Redundancy of Independent Component Analysis in Four Common Types of Childhood Epileptic Seizure

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Summary: Independent component analysis (ICA) has recently been applied to epileptic seizure in the EEG. In this paper, the authors show how the fundamental axioms required for ICA to be valid are broken. Four common cases of childhood seizure are presented and assessed for stationarity and an eigenvalue analysis is applied. In all cases, for the stationary sections of data the eigenvalue analysis yields results that imply the signals are coming from a source-rich environment, thus yielding ICA inappropriate when applied to the four common types of childhood seizure. The results suggest that it is not appropriate to apply ICA or source localization from independent components in these four common cases of epilepsy, because the spurious independent components determined by ICA could lead to a spurious localization of the epilepsy. If surgery were to follow, it could result in the incorrect treatment of a healthy localized region of the brain.

Key Words: Independent component analysis, Childhood, Epilepsy, Redundancy, Blind source separation.

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A typical EEG consists of roughly 16 to 25 electrical recordings from sensors at different locations on the scalp. Each recording represents a complicated linear mixture of signals (Nunez and Katzelnelson, 1981) responsible for various brain activities that a consultant has to interpret. In the case of epilepsy, it is particularly hard to locate the origins of the epileptiform discharges that occur in the onset of an epileptic attack. The signal processing technique of linear independent component analysis (ICA) (Cardoso, 1989; Comon, 1989) holds promise for such a decomposition to be realized. A single publication (Kobayashi et al., 1999) applied linear ICA to isolate epileptiform discharges of a partial seizure from the unaveraged EEG.

In this previous study, two epileptic components were isolated (as spike and slow wave components). The work of Kobayashi et al. is of particular interest because it is the spike that lies within the spike and wave component that is responsible for a partial epileptic seizure. If the spike and the wave component, typical of a partial seizure, consist of two separate distinct sources, then the spike could be localized to a specific region of the neocortex. Conversely, it is also plausible that the ICA algorithm could separate the spike component from the wave component, but such a separation may be spurious and not due to a real separation of sources in the brain. If this is the case, then a localization of an independent component (IC) that does not exist would arise. If surgical treatment were to follow, a healthy localized region of the brain could be incorrectly treated.

METHOD

Independent Component Analysis

Linear ICA is a signal processing technique that allows one to statistically separate original signals from their mixture. The cocktail party problem highlights the possibility of how linear ICA could be applied to the EEG.

The Cocktail Party Problem

Consider a group of people talking at a party (Fig. 1). An observer could walk around the room and listen in on the conversation. Even though the same information exists in the conversation, the conversation would sound different to the observer at different positions around the room. This is due to the observer's relative distance from the speakers. By recording the same conversation from many different positions in the room, it is possible to statistically demix the original speakers voices from the conversation. This is the foundation of ICA theory.

It has been supposed that the signals from the neurons in the brain could be likened to the speakers in the room (Fig. 2). The signals from the brain linearly combine (Nunez and Katznelson, 1981) at the scalp to create a mixed signal that is a superposition of the original signals. A typical EEG record consists of 16 to 25 electrical recordings taken from scalp electrodes that are placed uniformly over the head of the patient as described by the 10:20 convention (Tyner et al., 1983) Thus, can one apply ICA to the EEG?

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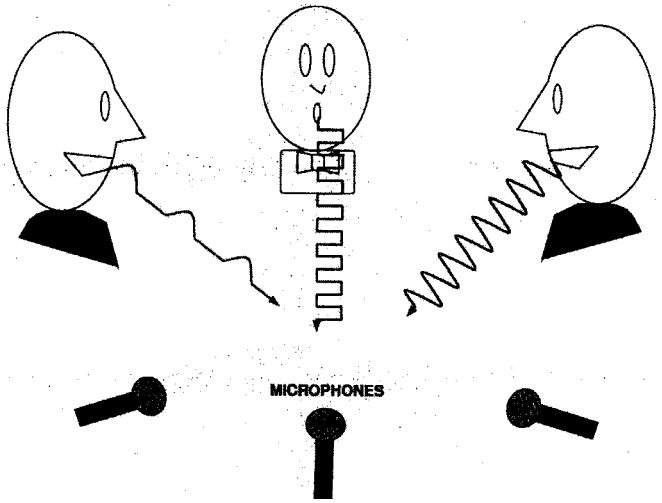

FIGURE 1. Schematic of the cocktail party problem.

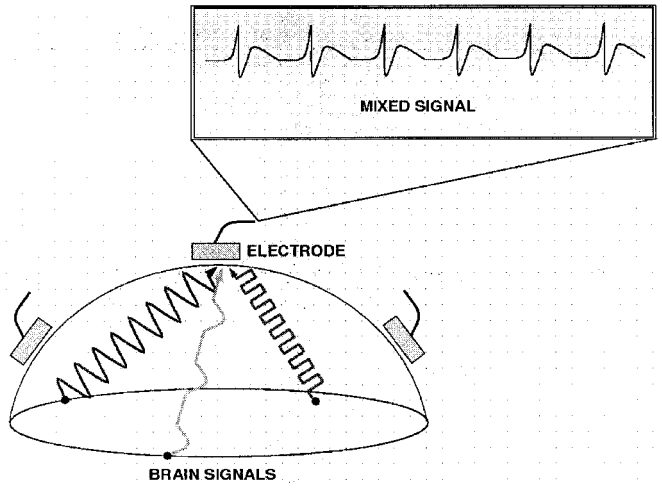

FIGURE 2. Schematic of the superposition of brain signals at the scalp.

Rules of Linear ICA

Linear ICA can separate signals from their mixtures if four rules are upheld: 1) the mixing matrix is constant; 2) the number of sensors is equal to or greater than the number of sources; 3) the mixing is cumulative (or a linear superposition); 4) and no reflections exist.

The first rule of ICA holds once regions of stationarity in the data are located. This can be achieved by performing stationarity tests on the data (Challis and Kitney, 1991). Once the stationary data have been located, an eigenvalue analysis (Rencher, 2002) is performed on the stationary sections. The second rule of ICA is determined by looking for a sharp drop in the power of the eigenvalues of the data. This locates the number of sources that exist in the data. The third rule of ICA is assumed from research in the literature that the signals of the brain superposition together linearly at the scalp (Nunez and Katznelson, 1981). The fourth rule is also assumed. In EEG, volume conduction from sources to electrodes would essentially be instantaneous, and the effects of the layers of scalp, skull, and CSF should be confined to changes in the mixing matrix (although frequency-dependent attenuation may occur when capacitive effects are incorporated in addition to resistive effects (Ferjallah et al., 1996). In this article, we reassess the methodology used in the 1999 study of Kobayashi et al. for a number of partial and generalized epilepsies and hence determine the applicability of ICA to the EEG for 4 common types of seizure.

DATA INVESTIGATED

The EEG multichannel data were provided by the Department of Pediatric Neurosciences at the Royal Hospital for Sick in Edinburgh. The data were drawn from a vast database that can provide epileptic EEG data from 2,500 existing records of some 500 patients. From these records, partial and generalized childhood epileptic discharges were investigated. The EEG instrument received the analog signals from 21 electrode sensors. Using analog filters, the EEG instrument 100-Hz low-pass filtered and 50-Hz notch filtered (to remove mains hum) the signals. The analog signal was then digitized at a sampling rate of 167 Hz. The electrode sensors were placed according to the International 10:20 system (Tyner, 1983), using the reference electrode, C_Z. These data sets were not used in any previous studies that have tried to apply ICA to the case of epilepsy. The data were displayed using MatLab software (*http://www.mathworks.com/*).

Four data sets were analyzed in this investigation. Each data set came from one of four types of common seizure now described. Some data sets were chosen from partial seizures. These seizures are localized to only a few channels of the EEG record. It was this form of seizure that was reported in (Kobayashi et al., 1999) and is known to have a characteristic spike/wave profile. The rest of the data sets used in the investigation were from three other common types of seizure. These were generalized seizures, which fall into the two categories: primary generalized seizures and secondary generalized seizures. The primary generalized seizures are split into two further types: primary typical generalized seizures and primary atypical generalized seizures.

STATIONARITY

A signal is said to be "strongly stationary" when the mean autocorrelation function, which implies variance, and all higher-order moments of the signal do not change, or remain stationary, with time. Strongly stationary signals do not occur in real-world systems. Thus, in real-world systems the word "stationary" (Challis and Kitney, 1991) implies a system that is defined as "weakly stationary," where the mean and variance are constant.

When one observes an EEG, the observed output signals are made up of hidden input signals and a hidden mixing matrix. The hidden input signals are signals that emanate from sources in the brain and can be stationary or nonstationary as described above.

The hidden input signals travel various distances from their source, through the neocortex to the electrode sensors.

The mixing matrix is used to store the distances from the input sources to the electrode sensors and also includes an attenuation constant that is a function of distance. The mixing matrix can also be stationary or nonstationary. It is defined as constant, or stationary, if the distance between the sources and the electrode sensors does not change with time. Namely, the sources are static and do not move. Conversely, the mixing matrix is said to be nonstationary if the distance between the sources and the electrode sensors changes with time. Namely, the sources' locations move as time evolves. Thus, the hidden input signals are linearly mixed, or linearly superpositioned, together by the mixing matrix at the electrode sensor to produce the observable output signals that can be either stationary or nonstationary.

Figure 3 describes the four different cases of stationarity that can be observed. Linear ICA can demix signals from their mixtures as long as the mixing matrix is constant, or stationary. As one can see, case 1 occurs when the mixing matrix is constant and the hidden inputs are stationary. The observed signals at the EEG will therefore be stationary signals and solvable by ICA. Case 2 occurs when the mixing matrix is constant and the hidden inputs are nonstationary. The observed signals at the EEG will therefore be nonstationary signals and solvable by ICA. Cases 3 and 4 occur when the mixing matrix is nonstationary and the hidden inputs are either stationary or nonstationary. The observed signals at the EEG will therefore be nonstationary signals which are not solvable by ICA. As one can see, cases 2, 3, and 4 all provide a nonstationary output, and even though case 2 is solvable by ICA, it is not possible to distinguish it from cases 3 and 4 because they are all nonstationary in nature. Therefore, we elected a conservative approach and only applied ICA to observable data that were stationary in nature to guarantee that the mixing matrix was constant.

To examine the issue of stationarity for the EEG, the mean power in the signal and the covariance of the multichannel data were investigated over a 2N window, where N represents the number of sensors. (A window of 2N is the minimum window size one can use to provide a robust measure of the covariance.) Areas where the power and covariance remained constant implied regions where the mixing matrix was constant and stationarity of source signals were constant.

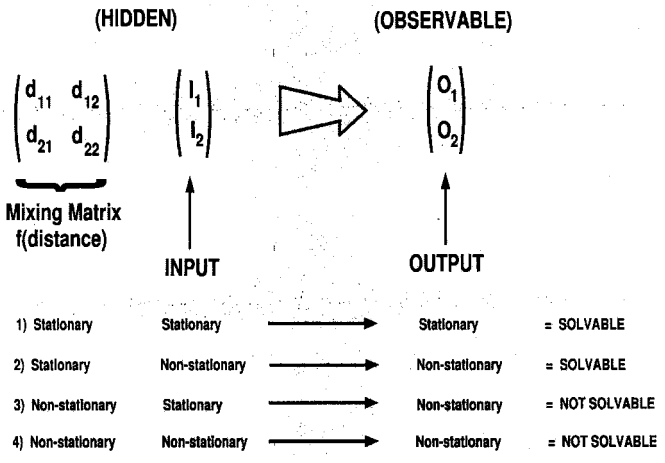

FIGURE 3. Schematic of Stationarity concept.

Locating Regions of Stationarity in the EEG Data

In the Kobayashi et al. study, three patients were examined. For each patient, 32 segments of EEG were concatenated together to form a data set. Each segment consisted of a whole epileptiform discharge and brief surrounding background. The number of points in each segment was 90, which was taken at a sampling rate of 200 Hz, representing 450 milliseconds. The total concatenated data length was 14.4 seconds. ICA was then applied to these sets of data.

Unsworth and colleagues questioned the methodology of Kobayashi et al. (1999) (Unsworth et al., 2002) and developed a new method (Unsworth et al., 2004; 2005) that was found to validate further the results presented in the current study. ICA can only be applied when the mixing matrix is constant or stationary. Any form of concatenation of this type could corrupt any form of continuity that exists in the mixing matrix and thus render ICA inappropriate. Application of ICA to such concatenated data sets could lead to very different demixtures as compared with the demixtures obtained by applying ICA directly to raw EEG data timecourses.

The authors decided to reexamine the stationarity of the mixing matrix for partial epilepsy that was examined in the study by Kobayashi et al. (1999) and also for three other types of common seizure.

Results: Partial Seizures

Figure 4, shows the multichannel EEG for a partial seizure. These seizures are localized to only a few channels of the EEG record. This form of seizure, the type that was reported in Kobayashi et al. (1999), is known to have a characteristic spike/wave profile. Figure 5, shows three plots. The upper plot is a spatial-temporal covariance plot (which will be referred to as the covariance from now on) of the multichannel EEG. The upper plot was obtained as follows. Assume that the data are arranged as in Fig. 4 (namely, the first channel represents the first row of data, the second channel the second, and so on). To calculate the covariance, at least 2N samples of data are required, where N is the number of electrodes. The calculation is started by taking a column of the first 2N samples of data (thus this column consists of the first 2N samples of the first channel, the first 2N samples of the second channel, and so on). This creates a $21 \times 2N$ matrix, which is then multiplied by its transpose to get a 21×21 symmetric covariance matrix. The first row, or first column, of this matrix describes the variance of all the channels relative to the first channel. This column is taken and normalized to the trace of the matrix (which is the power of the channels over the 2N interval). This normalized column then forms the first column of the upper plot and represents the spatial covariance of the 21 EEG channels relative to the first channel over the first time interval 2N. This is then repeated for each 2N time interval of multichannel data. Thus, the upper plot is built up column by column.

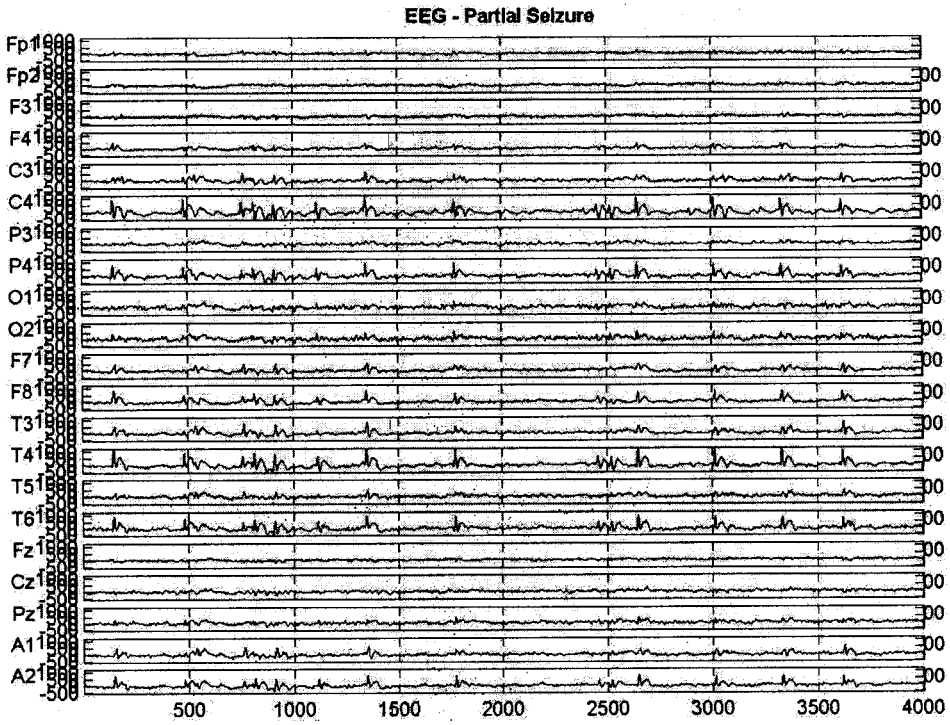

FIGURE 4. A partial seizure.

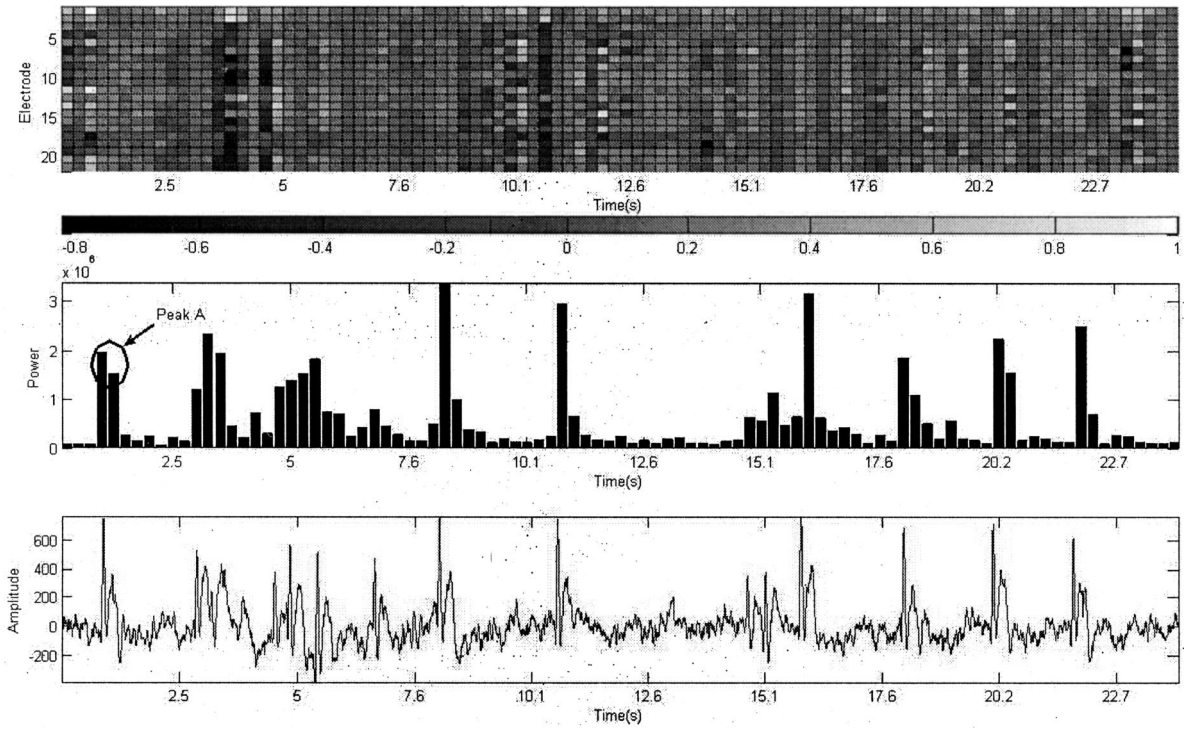

FIGURE 5. A partial seizure (c3561db5). *Upper plot:* Covariance plot (each window is 2N samples). *Center plot:* Mean power. *Lower plot:* Sample trace of one channel (for reference).

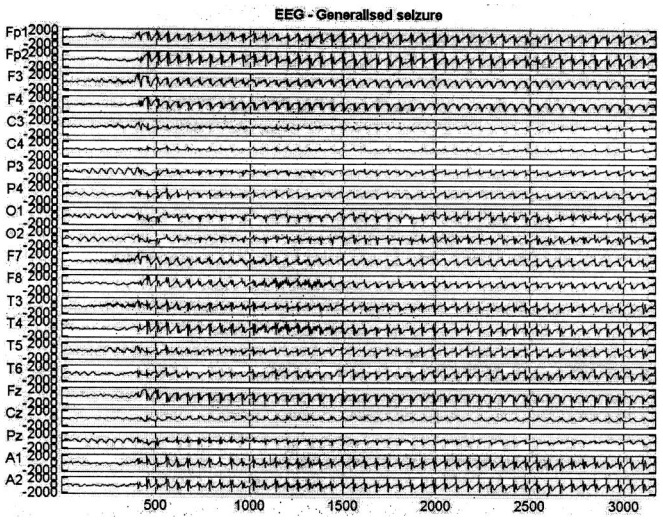

FIGURE 6. A generalized seizure.

To compare the upper plot temporally and spatially, the upper plot was normalized to the maximum value that occurred in all the columns of the upper plot. The middle plot is the mean power of all the channels at a specific time (t), and the lower plot is a plot of one of the EEG channels. This is to help the reader locate where in the signal that stationarity is occurring. As one can see, when a constant covariance is located the mean power is often not constant. Only over the epileptic spike/wave discharge did stationarity hold. Also it should be noted that this did not occur on every spike/wave occasion because the mean power would often fluctuate. When stationarity did occur, it was only for very short time intervals of 4N = 84 samples. The region labeled "peak A" was chosen to have the best stationarity on which to perform the eigenvalue analysis (described later). On the whole, the data could be considered nonstationary over the regions of epileptic seizure.

Results: Primary Generalized Typical Seizures

Primary generalized seizures are exhibited across all the channels of an EEG record. Each channel of the EEG exhibits a repetitive nonlinear profile which can be very different to the profiles of other channels. When the repetitive behavior is synchronous in all channels, the seizure is referred to as a typical generalized seizure or a typical absence seizure. Figure 6 shows the EEG record of a primary generalized typical seizure.

For the primary generalized seizures, larger data lengths were found in the body of the seizure. The section that best provided stationarity can be seen in window positions 61 to 67 (this region is framed by a rectangle that corresponds to 15.34–16.85 seconds) of Fig. 7, and provided 12N = 252 points of data on which to perform the eigenvalue analysis (described later).

Results: Primary Generalized Atypical Seizures

When the primary generalized seizure is asynchronous in all channels, the seizure is referred to as a primary generalized atypical seizure or primary atypical absence sei-

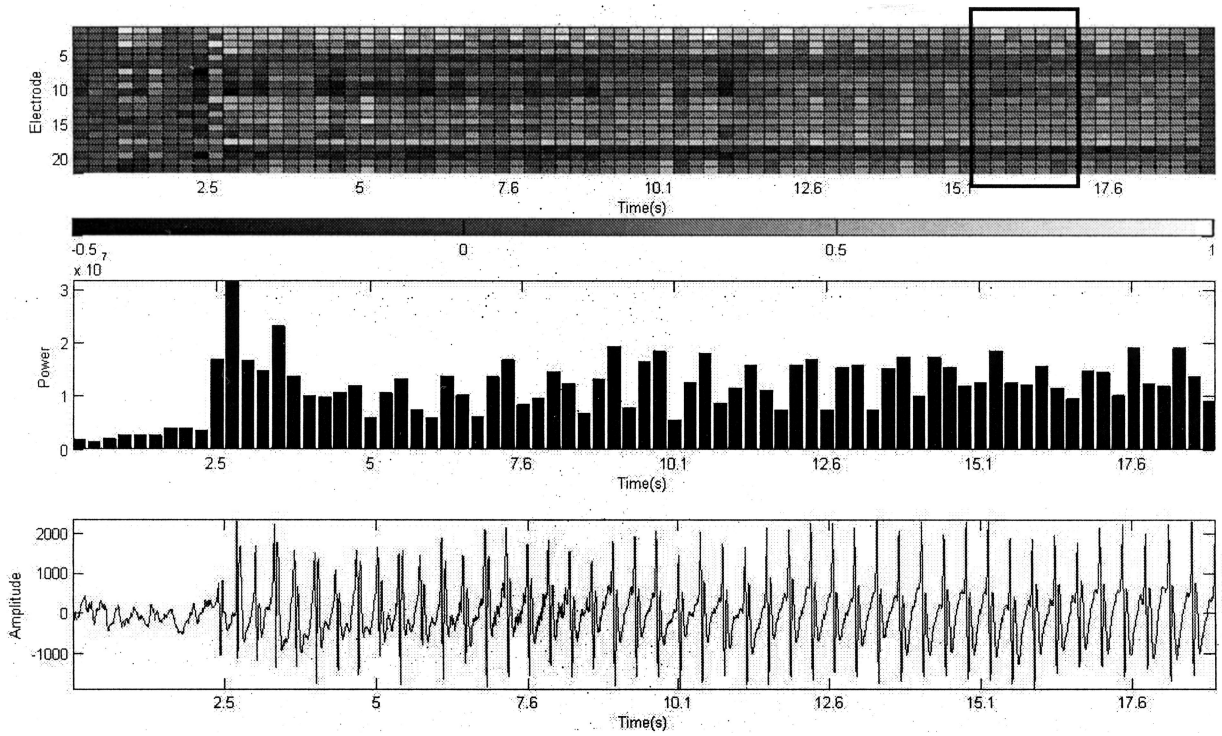

FIGURE 7. A generalized seizure (d665fd3c). *Upper plot:* Covariance plot (each window is 2N samples, where (N) is the number of electrodes). *Center plot:* Mean power. *Lower plot:* Sample trace of one channel for reference.

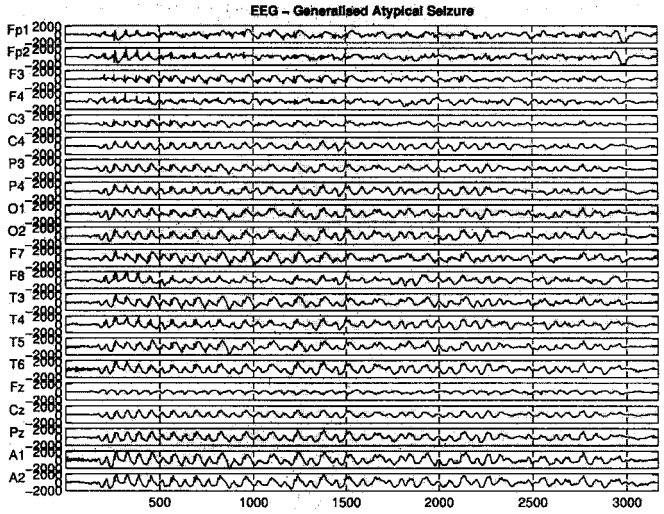

FIGURE 8. A generalized atypical seizure.

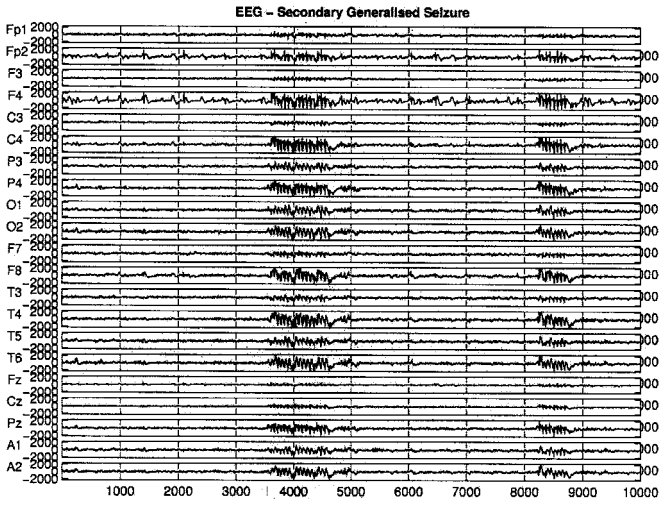

FIGURE 10. A secondary generalized seizure.

zure. Figure 8 shows the EEG record for a primary generalized atypical seizure. It can be seen in Fig. 9 that even though the covariance is constant, the mean power fluctuates a lot. Like the partial seizure, it is hard to locate regions of stationarity. The section that best provided stationarity can be seen in window positions 12 to 19 (this region is framed by a rectangle that corresponds to 3.02–4.78 seconds) of Fig. 9, and provided 14N = 294 points of data on which to perform the eigenvalue analysis (described later).

Results: Secondary Generalized Seizures

A secondary generalized seizure can be described as a partial seizure that generalizes across all EEG channels into a generalized seizure. Figure 10 shows the EEG data record of a secondary generalized seizure. It can be clearly seen that very large areas of constant covariance and mean power occur in Fig. 11. These areas correspond to the regions where the seizure generalizes. The section across window positions 33 to 43 (this region is framed by a rectangle that corresponds

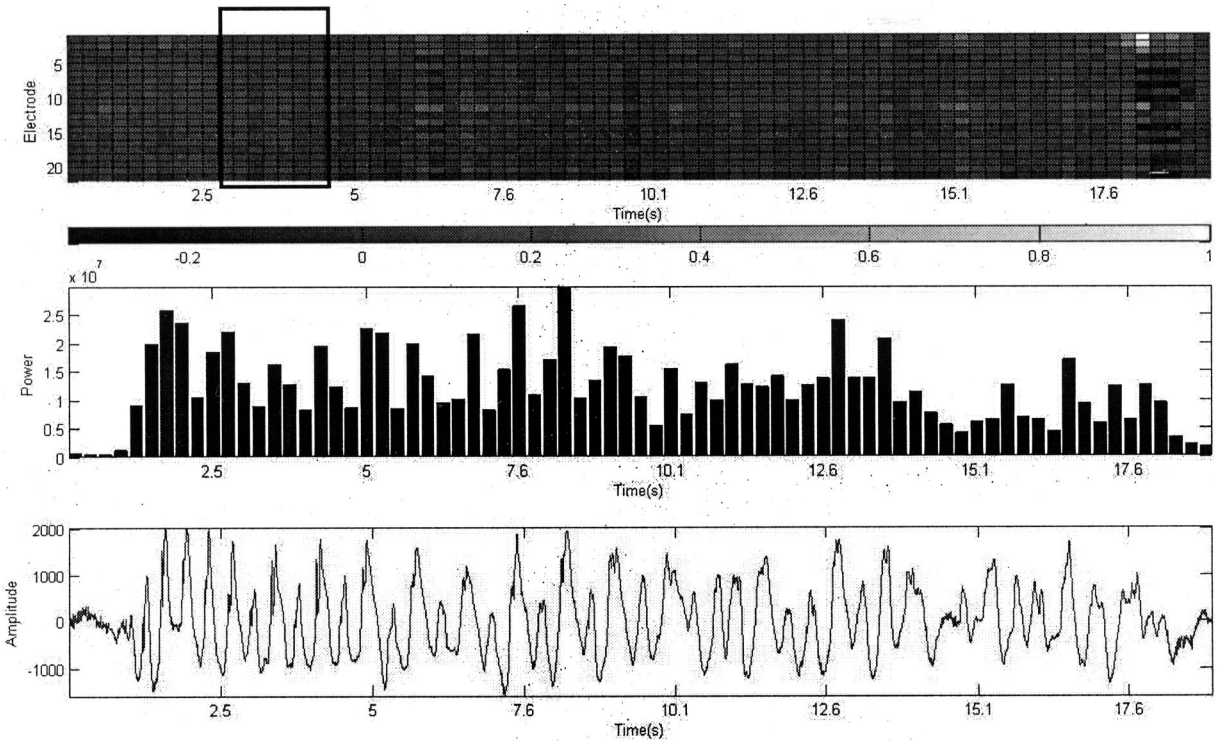

FIGURE 9. A generalized atypical seizure (sd50206): *Upper plot:* Covariance plot (each window is 2N samples). *Center plot:* Mean power. *Lower plot:* Sample trace of one channel for reference.

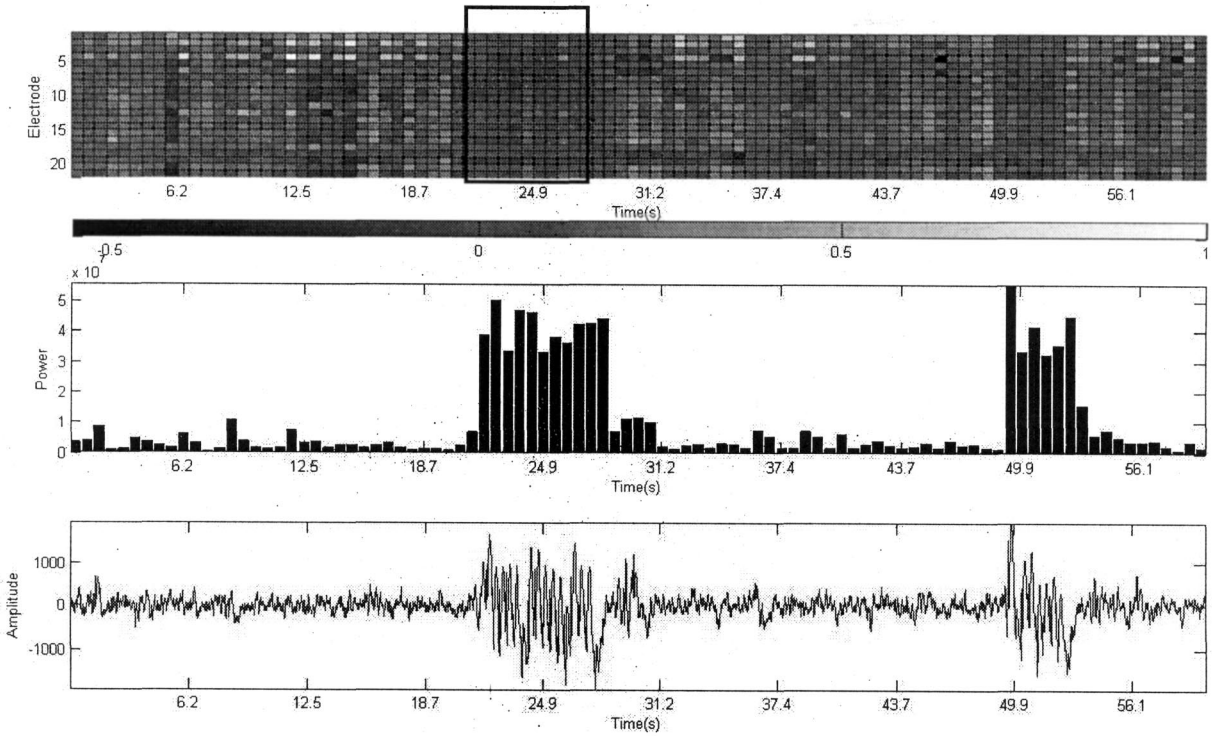

FIGURE 11. A secondary generalized seizure (sd50178). *Upper plot:* Covariance plot (each window is 5N samples). *Center plot:* Mean power. *Lower plot:* Sample trace of one channel for reference.

to 20.75–27.04 seconds) of Fig. 11, which provided 50N = 1,050 points of data (each window is 5N long, so 10 windows = 50N = 1,050 samples), where N is the number of electrodes, was chosen to perform the eigenvalue analysis on which is described in the next section.

EIGENVALUE ANALYSIS

In the article by Kobayashi et al. (1999), no attempt was made to determine the number of generating sources that existed in the EEG data. Instead the data were demixed using ICA for the maximum number of sources that could be conjectured. This was equivalent to the number of electrodes used, which was 25. Thus, the assumption that the number of sources was equal to the number of electrodes was being made. It is imperative to identify the number of sources that exist before using ICA to a given problem. Failure to do so will result in an ICA algorithm that returns a set of solutions that look very plausible but in fact have no meaning. It was our intention to examine this issue for the EEG when applied to epilepsy.

We elected to use an eigenvalue analysis approach (Rencher, 2002). Eigenvalue analysis can be used to determine the number sources that exist in a linear mixture. Such an analysis requires as a rule of thumb, 10N samples of data to give robust results. However, ≈5N samples of data will produce reliable results. The way one determines how many sources exist from such an analysis is to simply measure the eigenvalues that exist and to plot them in descending order of size. The location of the number of the sources that exist is where the power in the eigenvalue plot falls to zero.

Results: Eigenvalue Analysis of Partial and Generalized Seizures

Eigenvalue analysis (Rencher, 2002) was applied to the regions of data chosen in the previous sections (i.e., where the mixing matrix was found to be stationary). Figures 12 to 15 are the eigenvalue plots for the four seizures studied. For each

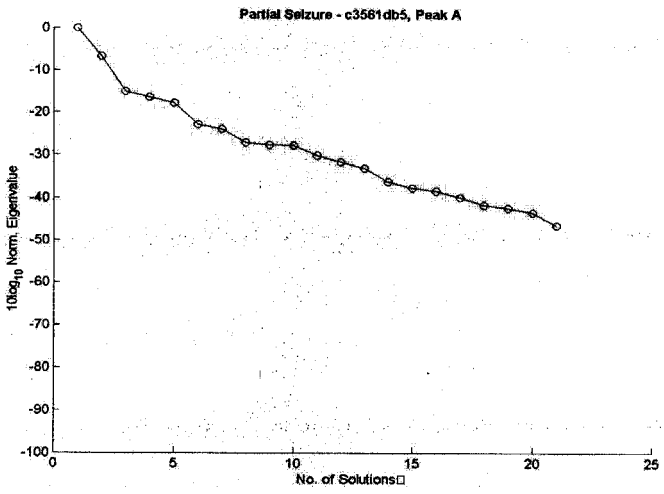

FIGURE 12. Eigenvalues for a partial seizure.

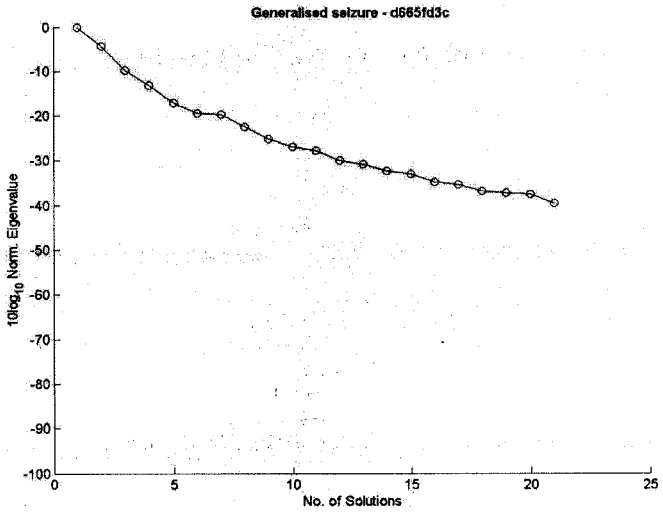

FIGURE 13. Eigenvalues for a generalized seizure.

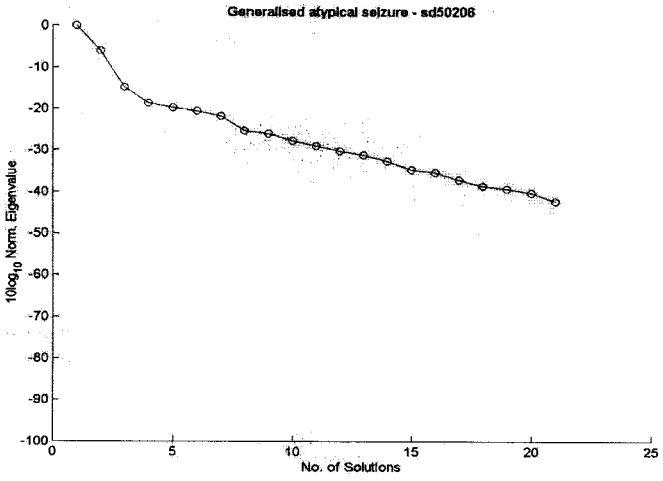

FIGURE 14. Eigenvalues for a generalized atypical seizure.

figure, the eigenvalues calculated were firstly normalized to the largest eigenvalue and then a $10\log_{10}$ plot of the normalized eigenvalues is displayed in rank order.

In the four different seizures analyzed, no sudden drop in the power of the eigenvalues, which locates the number of sources in the data, was found. Instead, a slowly decreasing level of power in the eigenvalues was observed. This implies that one could be examining a source-rich environment where there are many more sources than sensors. In addition, we applied the eigenvalue analysis across the whole data set to take into account the possibility of a constant mixing matrix and nonstationarity of sources (i.e., case 2, shown in Fig. 3). The same behavior was observed, implying a source-rich environment.

DISCUSSION

The work of Kobayashi et al. (1999) was reassessed and found to break many assumptions that are necessary for ICA to be valid. Stationarity tests were applied to identify

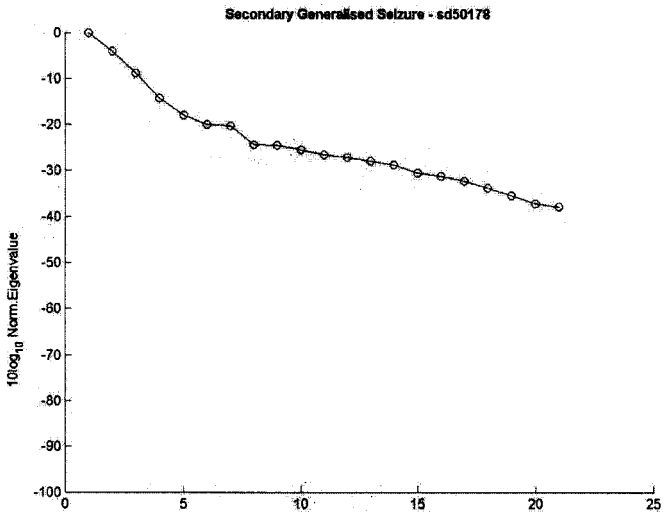

FIGURE 15. Eigenvalues for a secondary generalized seizure.

where the mixing matrix was constant for a variety of different epilepsies.

It was found that for partial seizures, stationarity very rarely held. When it did, ICA could be applied over the spike/wave region only, a small region 4N points. It must be noted that not all the spike/wave regions were stationary. An additional point to note is for this type of seizure, the stationarity of each spike/wave region must be assessed on its own merits, as not all spike/wave regions are stationary.

Primary generalized typical seizures were found to have stationary sections over 12N points.

Primary generalized atypical seizures were found to be stationary over 14N points. It must be noted that the primary generalized atypical seizure data, like the partial seizure data, had fluctuations in the stationarity and there was no predictable place in which stationarity could be guaranteed. Rather, each section of the primary generalized atypical data had to be assessed on its own merits.

For secondary generalized seizures, periods of stationarity of 20N samples were found. Reliable periods of stationarity were found to occur when the when the seizure generalized.

Overall, the secondary generalized seizure data had the most reliable and predictable areas of stationarity. The next most reliable data set for stationarity was the primary generalized typical seizures. It was very hard to identify regions of stationarity for partial and primary generalized atypical seizures.

Eigenvalue analysis was applied to the stationary sections of the seizure data. For all data sets a decreasing level of power in the eigenvalues was observed. This implies that one could be examining a source-rich environment, where there are many more sources than sensors. The same result was found when the analysis was applied across all of the data. No evidence was found to suggest that ICA could be applied to any of the four seizure data sets presented here.

This pilot study highlights the pitfalls of directly applying linear ICA to a given problem when the fundamental

axioms of ICA do not hold. Source localization techniques should not be applied to the demixed ICs, because this would result in further error and spurious prediction of where the sources originate from— if such sources exist at all.

More importantly, the results from this study suggest that it is not appropriate to use ICA or source localization from IC components in these four common cases of epilepsy. This is because the spurious ICs determined by ICA could lead to a spurious localization of the epilepsy. If surgical treatment were to follow, it could result in the incorrectly treatment of a healthy localized region of the brain.

Because this article presents the results from a pilot study, the conclusions are based on the analysis of four seizures only. The analysis of many more seizures from more patients should be performed to further validate the findings presented here.

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