Detecting Epileptic Seizure Activity in the EEG by Independent Component Analysis

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Abstract— **Manually reviewing EEG (Electroencephalogram) recordings, for detection of electrographical patterns, is a time consuming business. Therefore, the ability to automate the classification of interesting electrographical patterns is a good supplement to the wide range of detection algorithms currently used for EEG analysis. This paper presents the development of an algorithm for the detection and classification of epileptic activity in the EEG using Independent Component Analysis (ICA). Detection and classification of epileptic activity is achieved by an algorithm that searches for paroxysmal activity in the EEG. The number of underlying components and their activity is combined in one detection measure (absolute sum). When paroxysmal activity is detected, the estimated components are grouped in physiologically relevant clusters. These clusters are used to reconstruct a clean EEG signal, which can be evaluated again by the detection measure. The algorithm was designed using artificial EEG data constructed from known ICs. From evaluations it is seen that the absolute sum is a good measure to detect paroxysmal activity, resulting in a 74 % sensitivity and a 19 % selectivity. It is likely that these values will improve substantially if the estimated mixing matrix is used for the rejection and classification of artifacts. From this work it is seen that this ICA based algorithm has some great possibilities to detect and discriminate epileptic activity from several kinds of artifacts. This project gives a promising base for the development of a system that automates the classification of interesting electrographical patterns using ICA decompositions.**

Keywords— **Independent Component Analysis (ICA); EEG; Epileptic Seizure Detection; EEG Classification**

I. Introduction

In today's neurology research and clinical services, EEG recording is a commonly used diagnosing tool. Currently the detection of electrographic patterns, such as epileptic seizures is done by manually reviewing the EEG recordings. An algorithm that is able to detect and classify such electrographic patterns will be a good supplement to the wide range of all recently developed detection algorithms. This paper describes the usefulness of the recently developed decomposition method, ICA, for EEG classification.

A. EEG and Epilepsy

EEG stands for electroencephalogram and is a recording of the electrical activity generated by the brain. An EEG recording is divided into normal and abnormal patterns. An EEG is said normal if it lacks abnormal patterns known to be associated with clinical disorders. One of the most common known neurological disorders is epilepsy. Epilepsy is a symptom of excessive, disorderly, neuronal discharge, clinically characterized by discrete attacks (seizures) [1, 2]. Because seizures are not primarily electrographic patterns of characteristic morphology like spikes-and-waves, but rather behavioral events [3, 4], they are hard to capture using waveform parameters or template matching.

Since the abnormal EEG is superimposed on or intermittent with normal background EEG and EEG can be considered as a superposition of different membrane potentials, it is plausible that normal background EEG is composed of components different from those presenting EEG.

II. Methodology

Instead of capturing wave-form properties of an EEG segment, estimating the underlying components of an EEG segment can be an alternative way of classifying EEG patterns. The recently developed ICA method is developed for estimating underlying components of (multidimensional) statistical data.

A. Independent Component Analysis

The goal of ICA is to separate the original signals from their mixtures (1) with the only assumption that the original signals are statistically independent:

$$\mathbf{x} = \mathbf{A}\mathbf{s}, \tag{1}$$

where **x** is a data vector composed of n linear mixtures of n independent components (ICs) (**s**) with **A** the unknown mixing matrix [5]. The key to estimate the unknown mixing matrix by way of the inverse separation matrix is the measure of non-Gaussianity of the observed data vector. Following the Central Limit Theorem it can be seen that the less Gaussian the linear combination of the mixtures, the more independent the result of the transformation.

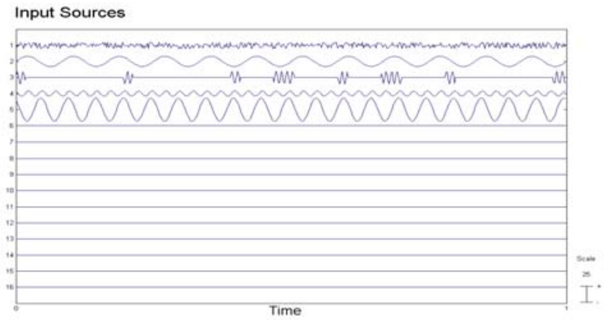
Application of ICA to EEG signals assumes that several conditions have been met: (*i*) the sources are independent, (*ii*) the propagation delays of the 'mixing medium' are negligible, and (*iii*) the number of independent signal sources equals or is less than the number of sensors [6]. Condition (*i*) is satisfied because the complexity of EEG dynamics can be modelled as a collection of statistically independent brain processes [7]. While most of the energy lies below 100 Hz, there is no need for introducing any time-delays so condition (*ii*) is satisfied [8]. Condition (*iii*) is important for the choice of the ICA algorithm, since we do not know the effective number of statistically independent brain signals contributing to the EEG recorded on the scalp.

A.1 ICA Algorithm

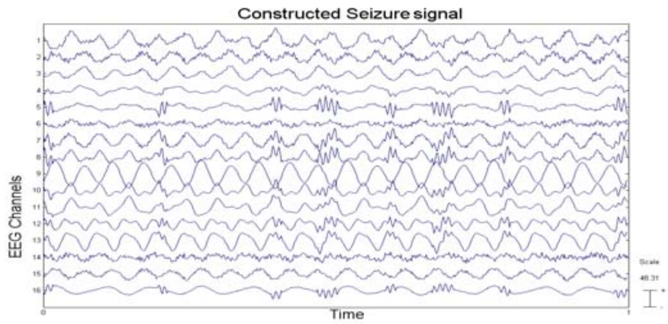
The choice is made between two major algorithms, Infomax [9] and Fast-ICA [10]. The Fast-ICA algorithm estimates ICs by hierarchical decorrelation in contrast to the parallel estimation of the Infomax algorithm. Disadvantages of the latter method originate in the unknown ICs building an EEG signal. The Infomax algorithm estimates always a predefined number of ICs in contrast to the Fast-ICA algorithm which terminates when all possible ICs are estimated (figure 1(c)). A major drawback of estimating individual ICs is that the order of components cannot be known in advance, so it is often necessary to perform complete decomposition. On the other hand the advantage of hierarchical decorrelation is a valuable counterbalance for mentioned disadvantage.

Following the ICA model in (1), it is seen that the algorithm's performance can be checked by comparing the chosen mixing matrix **A** with the estimated inverse mixing matrix (weight matrix) **W**. From (1) it is seen that, in case of a perfect reconstruction, multiplying mixing matrix **A** with weight matrix **W** results in the unity matrix **I** (figure 1(d)). While the order of estimated sources is not known and not constant (figure 1(a)), the estimated weight matrix has to be permutated.

The surface plot in figure 1(d) is not fully as expected. It is seen that the input sources which were not zero have been perfectly recovered. The side lobes in the figure are caused by the zero valued input sources, while it causes



(a)



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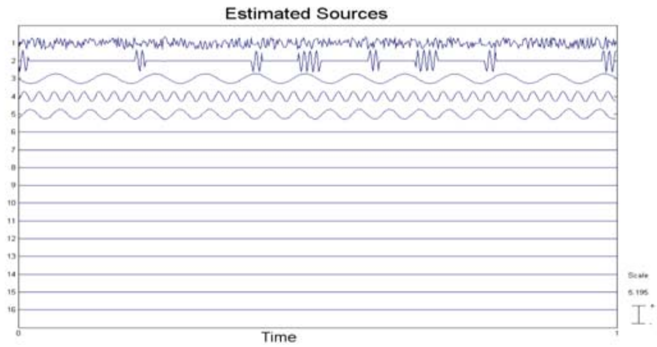

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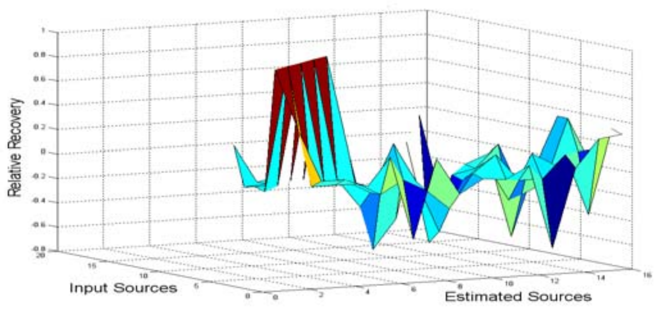


(d)

Fig. 1. This figure shows input sources used for testing the Fast-ICA algorithm. a). Sources used to construct an artificial seizure segment. b). An artificial seizure segment constructed using a random mixing matrix **A**. c). Estimated sources calculated with the Fast-ICA algorithm. d). Surface plot of the resulting Identity matrix.

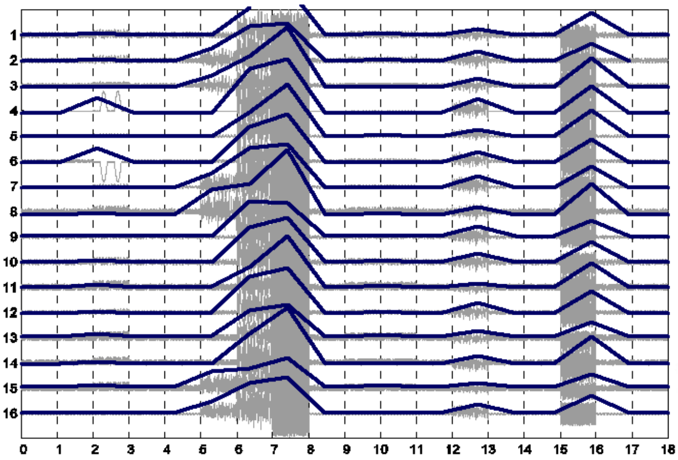


Fig. 2. This figure shows artificial EEG data with the absolute sum overlayed. The vertical grid is plotted on the boundary of every epoch, containing 512 data points.

some divide by zero errors showing up as not-a-number values in the calculated identity matrix.

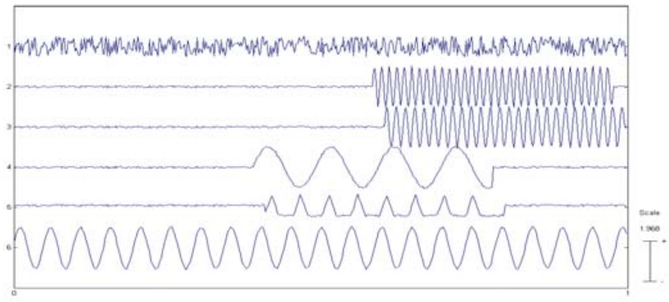
B. Detection of Abnormality

Looking at the more physiological meaning of the mixing matrix **A**, it can be said that the columns represent values of the individual components on every channel and the rows represent the values of all components on a single channel. Considering an abnormal EEG segment as a superposition of normal and abnormal EEG it is expected to see changes in a row of the matrix if an abnormality occurs in that specific channel:

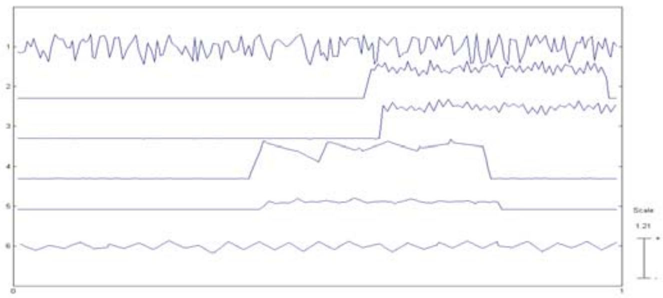
$$x_i = a_{i1}s_1 + a_{i2}s_2 + \ldots + a_{in}s_n, \tag{2}$$

for $i = 1, \ldots, n$. From the former and (2) it is seen that, considering the sum of the rows of matrix **A**, a measure for the alterations in the EEG signal is established. While the scaling factor of the estimated components cannot be exactly reconstructed, the absolute sum of the matrix entries is taken. If the assumption is made that a recorded EEG contains mainly background activity, the absolute sum will increase for epochs that contain paroxysmal events and will return to background level after the abnormality.

This hypothesis is tested using an artificial EEG data set. The data was divided into non-overlapping epochs, each containing 512 data points. For each epoch the mixing matrix **A** and the absolute sum were calculated. Figure 2 shows a peak for the absolute sum at every event. It is seen that the absolute sum gives a good measure for paroxysmal activity in every separate EEG channel.



(a) Constructed ICs to clarify the hypothesis of statistically independence and energy burst dependence. The segment size is 512 data points.



(b) Upper envelope of energy signals. Looking at these signals the correlation between the bursts is clearly seen.

Fig. 3. Explaining the difference between the statistically independency of the ICs in contrast to energy dependence. From this figure it is seen that components can be clustered using the cross-correlation between the components.

C. Clustering Components

The idea behind clustering is that the independence criterion applies solely to the statistical relations between the amplitude distributions of the involved signals and not to considerations upon the morphology or physiology of certain neural structures [11]. Instead of sorting the components clustering is used to group physiological relevant components. In figure 3(a) it is seen that the components of an artificial muscle burst can be statistically independent but their energy bursts are correlated.

Clustering of the components can be achieved using the cross-correlations between the components. As is seen in figure 3, channel 3 and 4 are highly correlated around $\tau = 0$, from which can concluded that they represent the same physiological event [12].

D. Artifact Rejection

In the recorded EEG there are two major artifacts: muscle and eye-movement artifacts. Muscle artifacts can be classified by examining the frequency spectrum. Because they have a frequency behavior above 20 Hz while seizure activity is around 4 Hz. For classifying eye-movement artifacts spatial context information is the most effective way,

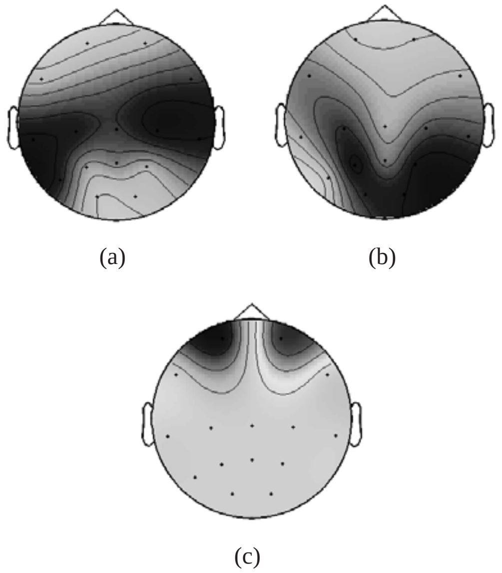


Fig. 4. From this figure it is clearly seen that when plotting the columns of the mixing matrix **A**, spatial context information can be used for artifact filtering. c). This figure shows the topographic map of an artificial eye-artifact segment.

while these artifacts are mainly recorded on the frontal channels. From (1) it can be seen that each estimated IC consist of a time course (**W**), and a scalp map (**A**).

By plotting a column of matrix **A** as a topographic map, using the known electrode locations. It is seen from figure 4, that an eye-blink component is only recorded on frontal channels.

III. Results

On forehand it can be concluded that the clinical evaluation of the detection algorithm at this moment is in a preliminary stage. The different methodology steps are evaluated using EEG data extracted from the Christchurch Hospital (Christchurch, New Zealand) database.

A. Test Data

Sixteen channels of EEG were recorded, via several bipolar and referential montages, from scalp electrodes placed according to the International 10-20 system. The amplified EEG was band was band-pass filtered between 0.5-70 Hz, sampled at 200 Hz and digitized to 12 bits. The performance was tested on EEGs (2.15 h) containing epileptiform activity from five patients ranging 5-65 years. The data contained 71 *true seizure events* (TSEs) defined as epileptiform bursts of 1 s or longer and marked by at least 2 of the 3 EEG experts as a definite or by one as a definite and 2 as a questionable. This data set was considered by one of the EEG experts to contain a sufficient number and variety of electrographic patterns to adequately test a

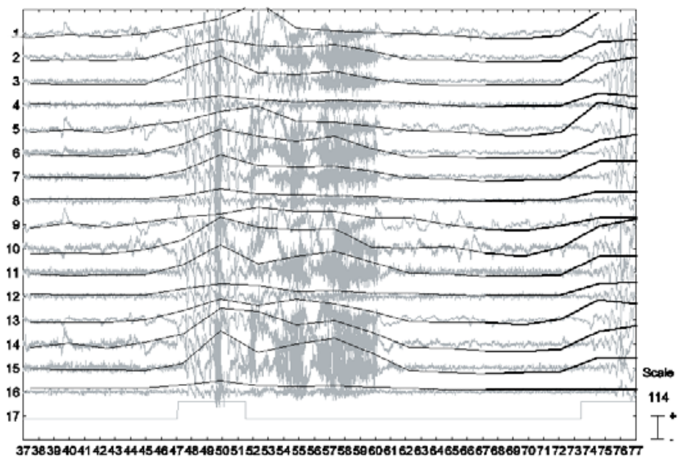


Fig. 5. This figure shows an EEG signal with clear seizures. The absolute sum is overlayed. Channel 17 represents the event channel. It is seen from this figure that the absolute sum can be used as a detection for clear seizure events.

seizure detection algorithm.

B. Performance

The different algorithm steps are evaluated in terms of sensitivity, selectivity and false detection rate.

$$\textit{Sensitivity} = \frac{\text{Total TPs}}{\text{Total TSEs}} \tag{3}$$

$$\textit{Selectivity} = \frac{\text{Total TPs}}{\text{Total TPs + Total FPs}} \tag{4}$$

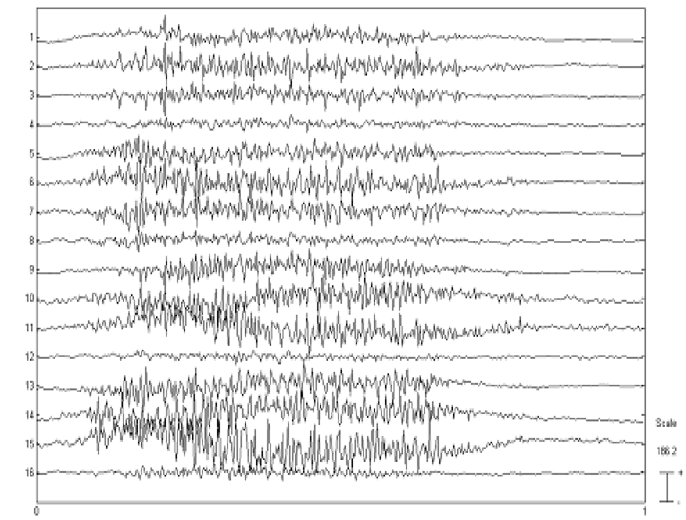
$$\textit{False detection rate = FPh} = \frac{\text{Total FPs}}{\text{hour}} \tag{5}$$

C. Detection of Abnormality

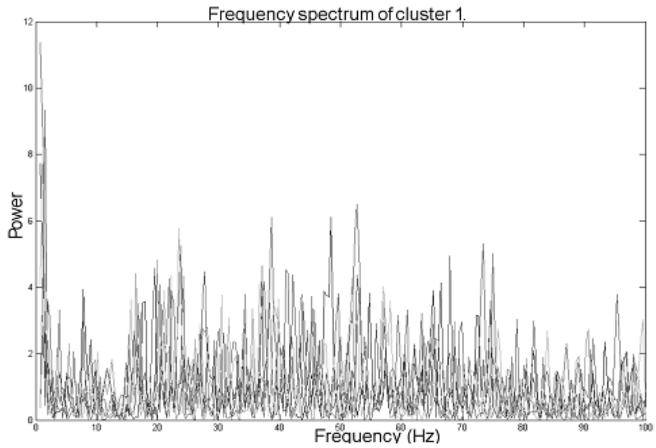
Figure 5 shows that the absolute sum is a good representative for the changing EEG signal. All seizure events can be detected, but it is also seen that not all maxima can be classified as an epileptic event. Therefore, the absolute sum can only be used as a preprocessing step for detecting paroxysmal activity.

The detection of paroxysmal activity is done using relative dynamic thresholds: absolute sum relative to the background. To obtain a clear background, epochs detected by the algorithm as paroxysmal were rejected from the background [12].

While at this stage rejected epochs are definitively removed from the evaluation it is necessary to chose a relatively low detection threshold. As expected the detection of paroxysmal activity performs with a good sensitivity (74 %) and a low selectivity (19 %).



(a)



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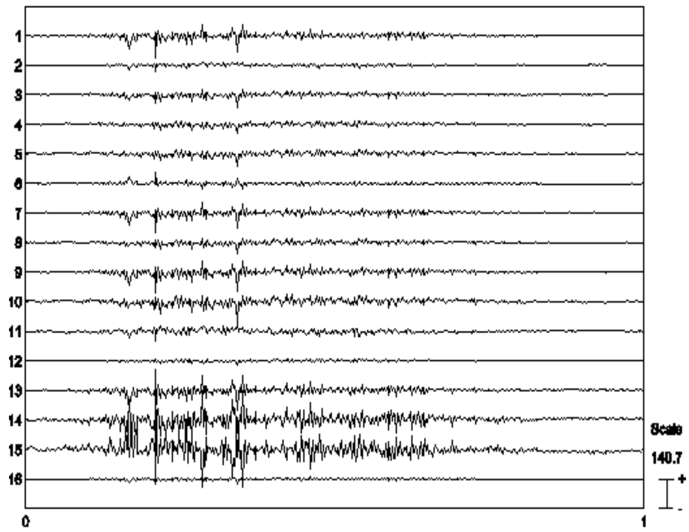

(c)

Fig. 6. These figures show the effect of clustering. It is seen that the EEG segment contains a burst of muscle artifact (a). (b) The result of the cluster of artifact components is characterized by its high frequency behavior. When this cluster is rejected by reconstructing the signal a clean EEG is constructed (c).

D. Clustering Components

Clustering should be used to substantially increase the selectivity of the algorithm. Currently this evaluation is in a preliminary stage but it does give some promising results.

Figure 6(a) shows an EEG segment disturbed by muscle activity. After estimating the mixing matrix the first 14 components show some clear high frequency behavior in contrast to the last 2 components. Clustering the components gave two clusters: (i) containing the background components and (ii) containing the artifact components characterized by high frequency behavior (figure 6(b)). After labeling this cluster as an artifact it can be rejected by the reconstruction so a clean EEG is obtained, as seen in figure 6(c).

Further research is needed to examine this way of clustering in detail and grouping the clusters into physiological relevant classes.

IV. Conclusions

From the detection of paroxysmal activity using the absolute sum it can be concluded that the abnormal EEG is indeed composed with different components than the background EEG.

Although it is hard to tell after such a preliminary evaluation, it is not expected that paroxysmal activity detection using the absolute sum gives necessary better results than the more classical detection methods.

However, ICA is not primarily interesting for detection. The advantage of the availability of both temporal and spatial context information in the mixing matrix **A** makes the use of ICA appealing for classification. Even though the evaluation is still in a preliminary stage clustering gives some promising results for grouping the ICs into physiologically relevant clusters. Using clustering for the separation of components passes the major drawback of ICA (unsorted components) and in combination with spatial context it is possible to reconstruct a clean EEG segment.

Future research should be focussed on clustering and classifying the artifact components. They can be ignored by the reconstruction so the resulting clean EEG can be evaluated again by a detection algorithm. This step is necessary, and will substantially improve the selectivity.

This paper shows that an algorithm using ICA for the discrimination of artifacts and classification of neurological disorders is achievable. Such an algorithm in combination with classical methods for detecting paroxysmal activity makes it possible to serve as an real-time detector which will improve the clinical service of EEG recording.

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