**35th Annual International Conference of the IEEE EMBS**
**Osaka, Japan, 3 - 7 July, 2013**

# Spatial correlation based artifact detection for automatic seizure detection in EEG

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***Abstract*—Automatic EEG-processing systems such as seizure detection systems are more and more in use to cope with the large amount of data that arises from long-term EEG-monitorings. Since artifacts occur very often during the recordings and disturb the EEG-processing, it is crucial for these systems to have a good automatic artifact detection. We present a novel, computationally inexpensive automatic artifact detection system that uses the spatial distribution of the EEG-signal and the location of the electrodes to detect artifacts on electrodes. The algorithm was evaluated by including it into the automatic seizure detection system EpiScan and applying it to a very large amount of data including a large variety of EEGs and artifacts.**

***Index Terms*— artifacts, automatic seizure detection, EEG**

## I. Introduction

Electroencephalograms (EEG) enable the analysis of brain activity by medical experts. EEG helps in particular to diagnose and monitor neurological pathologies such as epilepsy. EEG recordings are often contaminated by artifacts, which make the EEG less readable for a person or an automatic EEG processing system [1]. Artifacts can be physiological or non-physiological. Physiological artifacts can arise from eye movements or muscle activity. Non-physiological artifacts may e.g. come from the recording equipment, from interference of electric fields or from poor electrode contacts. Some of these artifacts are particularly disturbing for automatic EEG processing systems, which makes automatic artifact detection necessary. Automatic seizure detecting systems are particularly affected by artifacts that mimic pathological EEG. Most of the artifact detection techniques nowadays use thresholding techniques based on time-frequency features of the signal. Lower- and higher statistical properties of the EEG signal are used, as well as adaptive thresholding [2]–[12].

*This work was supported in part by HIGH PROFILE. The HIGH PROFILE project has received funding from the ARTEMIS Joint Undertaking under grant agreement n° 269356.

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The decomposition of the signal via independent component analysis (ICA) [10] or principal component analysis (PCA) [13] has proven to be a good way to separate the artifact from the normal EEG, but thresholding techniques are still needed to detect the artifact within the signal component and the techniques are computationally expensive. Also it is difficult to detect which electrode the artifact is coming from. In order to reduce only certain artifactual frequency components of the signal or the signal components obtained with ICA and PCA, the wavelet decomposition has been used [7], [9], [13]. Classifier methods based on support vector machines (SVM) [4] or linear discriminant analysis (LDA) [6] were investigated, but these methods have the drawback that they require a large amount of supervised data for parameter estimation prior to online processing. Some types of artifacts such as eye movements have been widely analyzed [3], [7] but are not the main disturbing artifact in automatic EEG-processing. For a seizure detection system it is naturally important to recognize artifacts that mimic the pathological EEG. These are particularly difficult to detect because their principal features do not differ much from the normal EEG. The usual thresholding techniques based on time- or frequency features do not suffice. It is necessary to take into account the spatial distribution of the signal. The signal coming from the brain has to match certain physical properties as for example a continuous distribution over the skull. Here, we are presenting an algorithm that uses the information of the location of every electrode in order to detect electrodes with artifacts that come from an extra-cerebral source. The way a signal should change over the adjacent channels is used as well as the location of the electrode and its adjacent electrodes. Our algorithm mimics the procedure of a medical expert when checking the EEG for an artifact. Using only the signals of predefined subsets of electrodes improves the robustness of the algorithm. The system works automatically, reliably and is computationally inexpensive. In order to evaluate the algorithm, it was included into the epileptic seizure detection system EpiScan [8] and applied to 5121h of unselected EEG from an epilepsy monitoring unit. It improved the seizure detection by reducing the false alarm rate by 39% on average, reducing the sensitivity only by 3%.

## II. Method

Our algorithm detects an electrode artifact in the EEG in the same way as a medical expert does. In Figure 1 an example of an artifact coming from one single electrode is shown in the longitudinal bipolar montage. The artifact is easily recognizable because it presents a clear phase reversal and the dominant pattern is only seen on two channels sharing the affected electrode. The pattern does not repeat itself on any other channel, therefore it is surely from an extra-cerebral source. In summary, two conditions need to be fulfilled to identify an artifact on an electrode:

1. Phase-reversal on the electrode in a bipolar montage
2. No repetition of the pattern on adjacent channels

Our algorithm detects an artifact on an electrode by checking these two conditions. For this, the EEG-signals of other channels are needed, but not all. As can be seen in Figure 2, where a zoomed picture of the artifact is shown, four adjacent bipolar channels, derived from five electrodes, suffice to recognize the signal as an artifact. In order to check the first condition (phase-reversal) only the two middle channels are needed and the checking of the second condition (absence of the pattern on adjacent channels) requires the four channels.

The EEG signals were recorded in the 10-20 system with additional epilepsy electrodes.

### A. Definition of electrodes sets

Since five electrodes suffice to recognize if the electrode has an artifact, we define for every electrode $i$ =1..N an ordered set $S_i$ of five neighboring electrodes with the electrode $i$ in the middle:

$$S_i = \{n_{i,1}, n_{i,2}, n_{i,3}, n_{i,4}, n_{i,5}\}, \text{ with } n_{i,3} = i. \qquad (1)$$

These sets represent a row of bipolar channels that can come from the longitudinal, the transverse or the circumferential montage. Figure 3 shows an example for the electrode C3. The set of electrodes for C3 is {FP1,F3,C3,P3,O1}, the set of bipolar channels is {FP1-F3, F3-C3, C3-P3, P3-O1}.

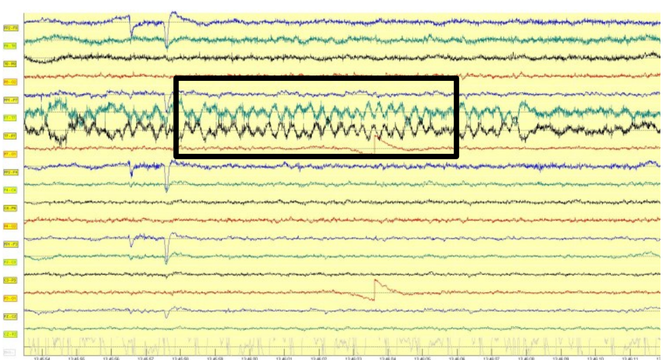

Figure 1: Example of artifact, seen in the longitudinal bipolar montage

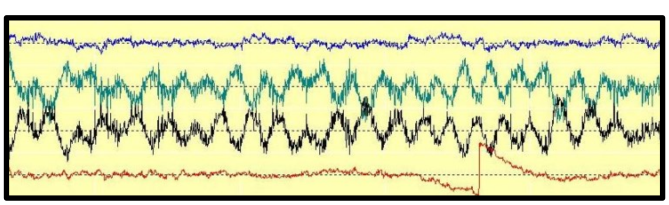

Figure 2: Zoomed artifact from Figure 1

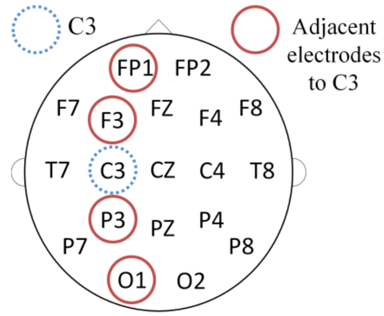


Figure 3: Representation of a set of electrodes $\boldsymbol{S_i}$ in the 10-20 system

### B. Calculation of coefficients

Each condition is checked by computing a different coefficient based on the set of EEG-signals and comparing it to a threshold.

We define $x_i(t)$ the signal of the electrodes $i$ =1..N. The vector $\underline{x_i}$ represents the samples of the signal $x_i(t)$ in a time frame of 1 second.

$$\underline{x_i} = \left(x_i(t_1), \dots, x_i(t_2)\right),\ t_2 - t_1 = 1 \text{ sec.}$$

$\underline{b_{i,j}}$ are the bipolar vectors resulting from the set $S_i$, defined in (1).

$$\underline{b_{i,j}} = \underline{x_{n_{i,j+1}}} - \underline{x_{n_{i,j}}},\ (j = 1..4).$$

#### 1) First condition: phase-reversal

The coefficient for this condition compares the EEG-signals of the two bipolar channels $n_{i,2}$ and $n_{i,3}$ that include the possibly affected electrode $i$. It is applied to the bipolar signals $b_{i,2}$ and $b_{i,3}$ which both include the signal of the electrode $i$. $p_i$ is a derived correlation coefficient that takes into account the amplitude of the signals dividing the covariance by the sum of the variances.

$$p_i = 1 + 2\,\frac{\underline{b_{i,2}}^T \cdot \underline{b_{i,3}}}{\underline{b_{i,2}}^T \cdot \underline{b_{i,2}} + \underline{b_{i,3}}^T \cdot \underline{b_{i,3}}}$$

If this coefficient is low, the two signals have very similar pattern and amplitude and opposite phase, matching the first condition of the algorithm.

#### 2) Second condition: no repetition of the pattern

For the second condition, the coefficient $f_i$ is computed. It is the maximum of the coefficients $f_{i,1}$ *and* $f_{i,3}$:

$$f_i = \max\left(f_{i,1}, f_{i,3}\right),$$

with

$$f_{i,k} = \left|\frac{\underline{b_{i,k}}^T \cdot \underline{b_{i,k+1}}}{\sqrt{\left(\underline{b_{i,k}}^T \cdot \underline{b_{i,k}}\right) \cdot \left(\underline{b_{i,k+1}}^T \cdot \underline{b_{i,k+1}}\right)}}\right|.$$

$f_{i,k}$ is the absolute value of the standard correlation coefficient. It does not take into account the amplitude, by dividing the covariance by the product of the standard deviations. $f_{i,k}$ is calculated based on the signals of two bipolar channels. If this coefficient is high, the two signals have very similar pattern, regardless of amplitude and phase. If it is low, the two signals do not have a similar pattern. $f_{i,1}$ is calculated with $\underline{b}_{i,2}$, that includes the signal coming from the electrode $i$ and $\underline{b}_{i,1}$ that does not. $f_{i,3}$ is based on $\underline{b}_{i,3}$ that includes the signal coming from $i$ and $\underline{b}_{i,4}$ that does not.

Hence, if $f_i$ is low, it means that none of the signals coming from the electrode $i$ correlate with the signal of an adjacent electrode to $i$. Thus, the dominant pattern coming from $i$ is not found on adjacent electrodes, matching the second condition of the algorithm.

*3) Definition of an alternative set of electrodes*

Since sometimes two adjacent electrodes could be affected by an artifact, we define for every electrode two different sets $S_i^{(1)}$, $S_i^{(2)}$. For example $S_i^{(1)}$ may include a series of electrodes from the longitudinal and $S_i^{(2)}$ from the transverse montage. The coefficient $p_i$ is calculated for the two sets $S_i^{(1)}$ and $S_i^{(2)}$. The lower value of $p_i$ decides which set is used in the following to calculate $f_i$.

## III. EVALUATION

The artifact detection algorithm was evaluated by applying the EpiScan system and measuring the performance with and without artifact detection.

### *A. Episcan*

EpiScan [8] is an online seizure detection algorithm for long-term EEG monitoring, which is based on the frequency-domain Periodic Waveform Analysis (PWA) and a time-domain analysis called Epileptiform Wave Sequence (EWS). PWA and EWS detect regular and irregular rhythmical EEG patterns. They are followed by an adaptation module automatically adjusting the algorithm to patient-specific EEG properties, which detect regular and irregular rhythmical EEG patterns.

### *B. Performance*

The performance of the seizure detection was estimated by calculating the average sensitivity and false alarm rate over all patients. For each patient the sensitivity was defined as the ratio of the number of correct detections to the number of seizures and the false alarm rate was the average number of false detections per hour.

### *C. Data*

The algorithm was applied to the EEG of 68 patients. All 68 patients went through a long-time monitoring on an epilepsy monitoring unit. Their recording lasted 1 to 8 days, on average 4 days, details are found in Table I. The patients had all types of diagnoses as can be seen in Table II. Most of them had temporal lobe epilepsy for which PWA, EWS and the EpiScan system works the best, since they frequently present rhythmical patterns. 28 of the patients had recorded epileptic seizures. In total 185 seizures were recorded. The patients had 1 to 32 seizures during the recordings and on average 0.2 to 15 seizures per day. All the 185 seizures where marked by trained medical experts.

TABLE I: RECORDING DURATIONS

| Recording time | Number of patients |
|---|---|
| < 1 day | 6 |
| < 2 days | 12 |
| < 3 days | 11 |
| < 4 days | 30 |
| < 5 days | 8 |
| < 9 days | 1 |

TABLE II: DIAGNOSES

| Diagnose | Number of patients |
|---|---|
| mesial temporal lobe epilepsy | 4 |
| temporal lobe epilepsy | 16 |
| generalized epilepsy | 2 |
| frontal lobe epilepsy | 6 |
| focal epilepsy | 14 |
| undefined | 14 |
| no epilepsy | 12 |

The EEG was unselected, no part of the data was cut out prior processing. Thus, all kinds of artifacts have occurred during the recording. Only the 50 Hz current hum was preprocessed with a notch filter.

## IV. RESULTS AND DISCUSSION

The artifact detection algorithm highly improved the automatic seizure detection system EpiScan by recognizing artifacts and therefore reducing the number of false alarms. On average, the false alarm rates of the patients were reduced by 39% while only 3% for the sensitivity 4 seizures were missed that had been detected before. With the artifact detection algorithm, EpiScan achieved an average false alarm rate of 0.41 FA/h with an average sensitivity of 69%. In comparison, EpiScan without the artifact reduction had a false alarm rate of 0.67 FA/h and a sensitivity of 72%.

Figure 4 shows the reductions of the false alarm rates (in %) for all patients. The mean reduction over all patients of 39% is represented by the horizontal dotted line. As can be seen in Figure 4, except for 2 datasets were the false alarm rate was already below 0.06 FA/h, a reduction of the false alarm rate of at least 8% and up to 100% was observed for all datasets. One dataset became false alarm free while its sensitivity stayed at 80%.

In Figure 5, a histogram is represented of the number of patients versus the false alarm rate. We can observe that 10 additional datasets dropped to a false alarm rate below 0.25 FA/h and only 2 datasets had a false alarm rate larger than 1 FA/h in contrast to 11 before artifact reduction.

Figure 6 shows a histogram of the number of patients versus the sensitivity. Here, we can see that the sensitivities of only 3 patients from 28 were affected. In total only 4 previously detected seizures were missed.

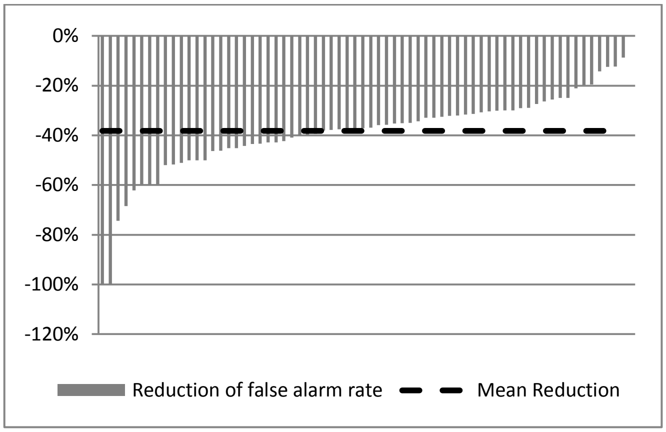


Figure 4: Reductions of the false alarm rates (in %) of the automatic seizure detection system EpiScan with artifact detection. Each vertical bar represents the reduction for a single patient.

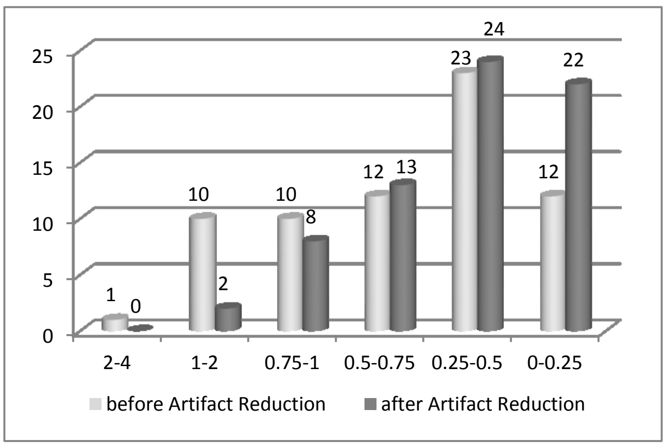


Figure 5: Histogram of the number of patients vs false alarm rate of the automatic seizure detection system EpiScan with and without artifact detection.

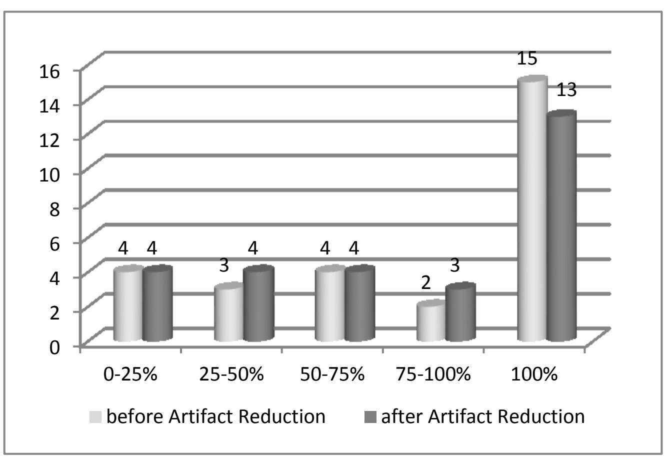


Figure 6: Histogram of the number of patients versus sensitivity of the automatic seizure detection system EpiScan with and without artifact detection.

## V. Conclusion

We presented an efficient automatic artifact detection system that uses the spatial distribution of the EEG for every electrode in order to detect electrodes with artifacts that come from an extra-cerebral source. The algorithm was applied to a large amount of data including a large variety of EEGs and artifacts. The results were used in the automatic seizure detection system EpiScan. The artifact detection algorithm improved very much the automatic seizure detection system. The false alarm rate was reduced by 39% on average from 0.67 to 0.41 FA/h while the sensitivity was only reduced by 3% to 69%.

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