Automatic muscle artifact removal as a preprocessing technique for seizure detection

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Muscle artifacts often deteriorate the quality of scalp EEGs, including at the onset of epileptic seizures. Therefore, this paper investigates the influence of removing muscle artifacts prior to automatic detection of epileptic seizures. Sensitivity, false detection rate and detection delay were compared between original and preprocessed EEGs. Removing muscle artifacts improved sensitivity (81% vs. 84%) and detection delay (12.6s vs. 10.8s), but increased false detection rate (0.74/h vs. 1.1/h). By only tuning the detection threshold a similar gain in sensitivity and detection delay could be reached, but resulting in a higher false detection rate.

Introduction

Long-term scalp EEG monitoring is one of the principal methods in presurgical evaluation of patients with refractory partial epilepsy. The recorded epileptic seizures contain valuable information about the epileptogenic zone in the brain. Automatic seizure detectors can alert patients, caregivers and the medical team at seizure occurrence. As patients themselves are not always aware of their seizures or not capable of warning the medical staff, these detectors can improve the diagnosis quality by alerting the staff much earlier in the development of the seizure. To be useful in clinical practice, high sensitivity, low false detection rate and small detection delay are required. Unfortunately, artifacts contaminating scalp EEGs deteriorate the performance of automatic detectors. As reported by Saab and Gotman [1], muscle artifacts are one of the causes of false detections and long detection delays. To circumvent this problem it was investigated whether automatic removal of muscle artifacts prior to seizure detection would improve the performance.

Materials and methods

Data selection

31-channel scalp data was collected from the Epilepsy Telemetry Unit at the Montreal Neurological Institute and Hospital, using the Stellate Harmonie System for EEG monitoring (Stellate, Montreal, Canada). Data were sampled at 200 Hz after band pass filtering between 0.5 and 70Hz. Scalp EEGs of 14 randomly selected patients were analyzed. For each patient, three types of data were included: 1) one containing normal activity, 2) one during sleep; and 3) all recordings with epileptic seizures. Each recording was on average 4h long, totaling 284h of analyzed EEGs.

Automatic muscle artifact removal

Muscle artifacts were removed by a blind source separation technique based on canonical correlation analysis (BSS-CCA) [2]. This technique linearly decomposes multichannel signals into sources that are uncorrelated with each other and have different autocorrelation structures. The sources are inherently sorted by their

autocorrelation coefficient (at lag 1). Hence, all sources containing muscle artifacts are grouped, as they have lower autocorrelation coefficients than all other activity [2]. To prevent incomplete separation due to time overlap of muscle artifact and slow activity, a 5th-order Butterworth high pass filter with 2 Hz cutoff frequency was applied before source decomposition. The contributions of the muscle artifact components were then subtracted from the unfiltered data, to prevent the loss of slow brain activity. The artifact components were selected based on their autocorrelation ordering and power spectrum. The average energy between 25 and 50Hz, most likely explained by muscle artifacts (*MuscleEnergy)*, was compared with that between 3 and 15 Hz, mainly affected by brain activity (*BrainEnergy)*: $Energy\ ratio = \frac{average(BrainEnergy)}{average(MuscleEnergy)}$.

The first component, starting from the least autocorrelated one, whose energy rate exceeded a certain threshold, was marked as the first component not containing muscle artifact. All components having a lower autocorrelation coefficient than this component were removed from the EEG. To determine an optimal threshold, energy ratios were calculated for several 10s-epochs of patients not included in this study. The threshold that best corresponded to visually classified components was retained and fixed for all further analyses.

Automatic seizure detection

For automatic detection of epileptic seizures, the online seizure onset detector from the Stellate Harmonie System was applied [1]. This detector calculates the probability that extracted features of a 2s-epoch belong to seizure activity, based on Bayes' formula:

$$P(seizure \mid features) = \frac{P(features \mid seizure)P(seizure)}{P(features)}$$

with P(x|y) the probability that x happens given that y happens and P(x) the probability that x happens. All probabilities on the right hand side are derived using previous training data [1]. The characterizing features are derived from 2-second (Daubechies-4) wavelet epochs. The detector diminishes false detections caused by muscle artifacts by reducing seizure probability if muscle artifacts are suspected. False detections caused by alpha activity are decreased by calculating the probability of alpha activity, similar to the seizure probability calculations. Finally, a seizure is detected when the sum of seizure probabilities over 3 consecutive epochs exceeds a threshold *Pth* unless the alpha probabilities exceeds a threshold *Ath*. Reported optimal threshold values are *Pth*=4 and *Ath*=2. Lowering *Pth* will cause more detections, which can improve sensitivity and detection delay, but deteriorate the false detection rate. All detections less than 30 seconds apart from each other were grouped as one.

Comparison

Both original and muscle artifact filtered data were analyzed by the detector with the standard probability threshold (*Pth*=4). For all patients, sensitivity, false detection rate and median detection delay were obtained. The overall performance was calculated as the average over all patients. The influence of preprocessing with BSS-CCA was compared with the influence of lowering the detector threshold to *Pth*=3 and 2.

Results

Automatic muscle artifact filtering reduced the average detection delay compared to normal filtering from 12.55 s to 10.84 s and increased average sensitivity from 81% to 84%. However, removing muscle artifacts increased false detection rate from 0.74/h to 1.1/h. For a similar gain in detection delay, tuning the detection threshold caused a higher false detection rate (1.36/h). If the detection threshold was lowered to *Pth*=2, the average detection delay dropped to 8.73s, but the false positive rate increased to intolerable 3/h. All results are summarized in table 1.

Table 1 Comparative results of the 4 detection systems.

	Sensitivity (%)	False detection rate/h	Median Delay (s)
Detector (threshold Pth=4)	81	0.74	12.55
BSS-CCA+ Detector(Pth=4)	84	1.10	10.84
Detector (threshold Pth=3)	85	1.36	10.87
Detector (threshold Pth=2)	90	2.94	8.73

Two seizures were only detected after removing muscle artifacts. By decreasing the detector threshold to 3 one of them was detected but only 4 seconds later. The other seizure was only detected after decreasing the detection threshold to 2. The sensitivity could not increase further by applying BSS-CCA, because all other undetected seizures were not particularly contaminated by muscle artifacts.

The gain in detection delay, when using BSS-CCA, was most often due to removal of muscle artifacts as shown in figure 1. In some cases only minor changes in fast activity were observed. The gain in detection delay by using BSS-CCA was not always the same as that obtained by lowering the detection threshold. If seizure onsets were only slightly contaminated with muscle artifact, the same gain could be reached by both adaptations. In cases of considerable contamination, only preprocessing by BSS-CCA could reduce the detection delay. If rhythms at seizure onset resembled alpha activity, only lowering the detection threshold could result in an earlier detection. In 2 seizures it was not clear why removing muscle artifact did not resulted in an earlier detection, as rhythmic ictal activity clearly became more prominent.

Most false detections were caused by short bursts of rhythmical activity. These rhythmical activities are also the main cause of extra detections when BSS-CCA is used, as the probability of detection of originally contaminated bursts is not penalized anymore by the detector system.

During analysis of the detections, it was observed that in a few cases some brain activity was removed. More commonly not all muscle artifacts were eliminated. In two of the analyzed seizures, an earlier detection of the onset could be achieved if the automatic selection of the components had been more optimal.

Discussion

Removing muscle artifacts from scalp EEGs can improve the detection of the onset of epileptic seizures using Saab and Gotman's automatic detector. However, more false detections were registered, mainly caused by originally contaminated rhythmical bursts.

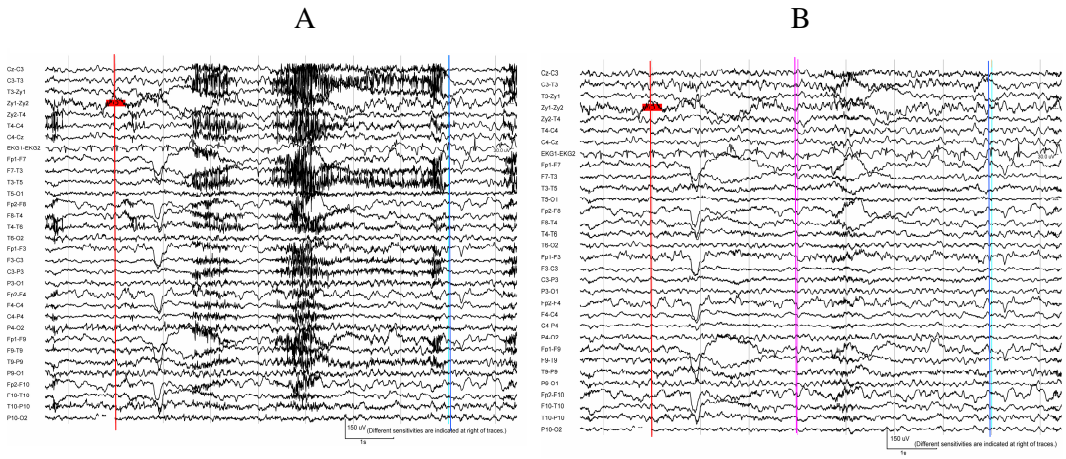


Figure 1 Illustration of an earlier seizure detection after removal of muscle artifacts. A: original 10-second epoch. The red line shows the seizure onset time, the blue line the detection for threshold Pth=4. B: the same epoch after muscle artifact filtering. The pink line shows the detection after filtering.

To improve false detection rate, several adaptations could be made to the seizure detection system. As the removal of muscle artifacts causes additional rhythmical bursts to become visible in the data, the probability of encountering those activities becomes higher. Consequently, the probabilities derived from previous training data are not optimal. In general, preprocessing modifies the data and the features characterizing the data. Retraining the seizure detector on preprocessed data could improve the detection system. The retraining could probably also improve sensitivity or detection delay in some other cases.

However, retraining alone will probably not reduce the false positive rate relative to the original system. More or other features could be more appropriate as most fast activity is eliminated from the data. False detections should be investigated more closely, and could be handled by the detector similar to the way muscle artifacts are penalized.

In addition to adaptations of the detection algorithm, the automatisation of the muscle artifact removal method itself should also be improved. In some cases, insufficient filtering prevented earlier onset detection, and in a few cases too much muscle artifact was removed. More data should be used to obtain optimal separation criteria and thresholds.

Nevertheless, using BSS-CCA as a preprocessing technique is already a valuable alternative to lowering the detection threshold if a low detection delay is required. A lower detection delay can be reached for a smaller increase in false positive rate.

[1] M.E. Saab and J. Gotman, ”A system to detect the onset of epileptic seizures in scalp EEG”, Clinical Neurophysiology, vol.116(2), pp. 427-442, 2005.

[2] W. De Clercq, A. Vergult, B. Vanrumste, W. Van Paesschen, S. Van Huffel, ”Canonical Correlation analysis applied to remove muscle artifacts from the electroencephalogram”, accepted for publication in IEEE Transactions on Biomedical Engineering.