ARTEFACT PROCESSING OF THE SLEEP EEG IN THE "SIESTA"-PROJECT

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Abstract: Artefact processing is an important issue in automated analysis of the sleep EEG. Nine artefact types were identified and their frequency of occurrence was analysed in 15 all-night sleep recordings from eight European sleep laboratories. Three artefact detection methods were evaluated with the area-under-ROC-curve (AUC), eight artefact minimisation methods were validated visually. Recommended methods are overflow detection, adaptive inverse filtering for movement and muscle detection, adaptive FIR filtering for ECG minimisation and 50Hz notch filtering.

Introduction

The aim of the SIESTA project is to build an automated sleep analysis system. Many types of artefacts can occur and many methods for dealing with artefacts in the sleep EEG have been published [1].

Materials and Methods

Nine types of artefacts (EOG, ECG, muscle, movement, failing electrode, sweat, 50/60Hz mains interference, breathing, pulse) were distinguished in the sleep EEG. Experts classified 7 EEG channels of 90 minutes segments of fifteen recordings from eight different sleep laboratories. A special viewer for scoring these artefacts based on a time resolution of one second was developed. The data was scored once, no re-scoring or consensus scoring was performed. The sampling rates of the recordings were 100, 200 and 256Hz.

The following processing methods were examined: (M1) adaptive finite impulse response filter using the Least Means Squares algorithm (LMS), (M2) regression analysis, (M3) principal component analysis (PCA), (M4) Independent Component Analysis (ICA), (M5) median filter, (M6) notch filters, (M7) phase space embedding filters, (M8) adaptive inverse filtering, (M9) moving average filters and band pass filters combined with a linear discriminant classifier, and (M10) overflow check. The methods were validated for their ability to detect or remove the artefacts listed in Table 1.

Two types of artefact processing methods were distinguished: the minimisation methods (M1-M7) were visually checked, the detection methods (M8-M10) were validated by the Receiver-Operator Characteristics (ROC) curve.

Results

Table 1: Overview of artefacts. 15 recordings, approx. 90 minutes each, with 7 EEG channels (563 192 epochs of 1s) were scored for 9 types of artefacts.

Code	Type	epochs [1s]	%
A0	no artefact	345 254	**61.3**
A1	EOG	51 427	**9.1**
A2	ECG	123 886	**22.0**
A3	muscle	43 861	**7.8**
A4	movement	20 209	**3.6**
A5	failing elect.	10 804	**1.9**
A6	sweat	4 135	**0.7**
A7	50/60 Hz	11 608	**2.1**
A8	breathing	2	**0.0**
A9	pulse	-	**0.0**
	SUM	611 186	**108.5**

M1. *Removing ECG with adaptive FIR filtering*
The basics of the method were presented in [3]. A normalised LMS algorithm was used to estimate the filter taps. The number of filter taps and the forgetting factor were chosen 1.05 times the

sampling rate and 0.01, respectively. Visual analysis yielded satisfying results for ECG minimisation.

M2. *Removing EOG and ECG with egression method*
Based on the all-night recordings the covariance matrix, and the regression coefficients between EEG, ECG and EOG channels were calculated. Visual analysis of the results did not give satisfying results for EOG removal but useful results for ECG removal.

M3. *Removing EOG with PCA [5]*
A crucial point was automating the segment selection for calculating the regression coefficients. Several methods (all-night, EOG>50µV, EOG>150µV) were investigated; none of them gave satisfying results.

M4. *Removing EOG with ICA [4*]
Visual analysis of a first implementation did not give satisfactory results. However, there is still some potential for improvement.

M5. *Removing muscle artefacts with median filter*
The idea was to smooth outliers caused by muscle artefacts. Visual inspection showed a disturbed EEG signal.

M6. *Removing 50/60Hz mains interference (Notch)*
In many recordings 50 Hz was observed. Therefore, it is recommended to apply a 50 Hz notch filter previous to signal processing.

M7. *Removing sweat artefacts with phase space embedding*
High-pass filtering was applied. Visual inspection showed that not only eye-movement components but also slow EEG components like K-complexes and delta waves were removed.

Table 2: Area under the ROC curve (AUC) for expert scoring and detector output; an AUC equal to 0.5 yields no correlation between the detector output and the artefact type. The larger AUC the larger is the discriminating power of the detector.

Code	AIF (M8)	BP+LD (M9)	OFC (M10)
A0	0.352	0.433	0.437
A1	0.651	0.629	0.370
A2	0.481	0.374	0.613
A3	0.857	0.834	0.546
A4	0.898	0.863	0.582
A5	0.553	0.503	0.662
A6	0.469	0.453	0.378
A7	0.477	0.457	0.310
A8	-	-	-
A9	-	-	-

M8. *Adaptive Inverse Kalman filtering*
Kalman filtering was used to estimate an adaptive autoregressive parameters [6]. The mean squared error (MSE) of the inverse filter process, based on 1s-epochs was used as output; The AUC (Table 2) showed that it is a strong indicator for muscle or movement artefacts.

M9. *Spectral analysis + Linear Discriminant Analysis*
The bandpower of four selected frequency bands was calculated and classified with LDA; the artefact scorings of the experts were used for learning and for validation. The ROC results are slightly worse than in M8.

M10. *Overflow detection*
Based on the histograms [2], saturation values were identified visually. The ratio of samples of each 1s-epoch that exceed the saturation values were used as output.

Discussion and Conclusions

Artefact processing produces never perfect results; some methods e.g. median filter removed not only the artefact but modified the signal, other methods e.g. PCA and BP+LDA could not be automated. Therefore, it is important to prevent artefacts; several methods are suggested in [1].

Artefacts were observed very frequently. In 38.7% of the recording time at least one artefact was identified. Therefore, artefact processing is important in an automated sleep analysing system.

At a first step, adaptive inverse filtering for muscle and movement artefact detection, overflow detection, regression analysis and adaptive FIR filtering for ECG minimisation and 50Hz Notch filters will be applied in the SIESTA project, while ICA for EOG-minimisation is still under investigation.

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