Automatic Processing of EEG-EOG-EMG Artifacts in Sleep Stage Classification

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Abstract — **In this paper, we present a series of algorithms for dealing with artifacts in electroencephalograms (EEG), electrooculograms (EOG) and electromyograms (EMG). The aim is to apply artifact correction whenever possible in order to lose a minimum of data, and to identify the remaining artifacts so as not take them into account during the sleep stage classification. Nine procedures were implemented to minimize cardiac interference and slow ondulations, and to detect muscle artifacts, failing electrode, 50/60Hz main interference, saturations, highlights abrupt transitions, EOG interferences and artifacts in EOG. Detection methods were developed in the time domain as well as in the frequency domain, using adjustable parameters. A database of 20 excerpts of polysomnographic sleep recordings scored in artifacts by an expert was available for developing (excerpts 1 to 10) and testing (excerpts 11 to 20) the automatic artifact detection algorithms. We obtained a global agreement rate of 96.06%, with sensitivity and specificity of 83.67% and 96.47% respectively.**

Keywords — **Artifacts processing, EEG, EOG, EMG, ECG.**

I. Introduction

While trying to automatically classify sleep stages, one is generally faced with the problem of artifacts. Indeed, artifacts contained in the analyzed polysomnographic signals introduce spurious components during features extraction, which lead to incorrect interpretation of the results [1]. Dealing with artifacts is therefore mandatory before any other classification operation.

In the literature, three main approaches have been proposed to detect and correct them. The first approach is based on autoregressive modeling [2, 3, 4] and is used for two purposes: (i) estimating the recorded EEG and identifies transient events like muscle or movement artifacts by locating the abrupt variations of the parameters; (ii) removing artifact from the EEG by estimating the parameters of the mathematical model that describe the recorded EEG as an overlap of the real EEG and the artifact interference.

The second approach uses standard voltage thresholds (overflow check) [4-5]. While these thresholds can sometimes be fixed (e.g 50μV), it is univocally accepted that using values related to the energy distribution of the signal in the frequency or time domain is preferable since voltage levels can strongly vary between subjects and recordings.

Finally, some authors investigated the use of independent component analysis (ICA) to remove the artifacts [6-7]. Unfortunately, their methods often required many EEG channels and implied to visually select the origin of the interference among estimated sources.

In the present study, we introduce algorithms for processing artifacts on EEG, EOG and EMG which are suitable for automatic sleep stages classification. The strategy is to imitate human behavior by locating the short duration artifacts so as to ignore them during the feature extraction stage of sleep stage classification.

However, cardiac interferences and slow undulations (e.g caused by breath interferences or by sweat) could not be processed using this strategy because these artifacts can last several hours. This is why we also developed two artifact correction algorithms in order to minimize the loss of data.

Nine procedures were finally implemented to remove cardiac interference and slow ondulations, and to detect muscle artifacts, failing electrode, 50/60Hz main interference, saturations, highlights abrupt transitions, EOG interferences and artifacts in EOG.

The performances of the algorithms were evaluated on a database of 20 polysomnographic sleep recordings scored in artifacts by an expert.

II. Materials and methods

A. Data

Data used in this study were recorded at the Sleep Laboratory of the André Vésale hospital (Montigny-le-Tilleul, Belgium). They are composed of 20 excerpts of 15 minutes-long polysomnographic (PSG) sleep recordings carried out during the night. The recordings were taken from 20 patients (15 males and 5 females aged between 31 and 73) with different pathologies (dysomnia, restless legs syndrome, insomnia, apnoea/hypopnoea syndrome). The sampling rates were 50, 100 and 200Hz. The 20 excerpts were visually examined by an expert to identify the various artifacts. Then they were separated into two groups for developing (excerpts 1 to 10) and testing (excerpts 11 to 20) the automatic artifact detection algorithms.

B. Artifacts detection/correction processes

Two procedures were developed to minimize cardiac interference and slow ondulations (*P1-P2*) and seven other procedures were implemented to indentify the remaining short artifacts (*P3-P9*). These detection algorithms operate on fixed length epochs (1.25 second by default). They are mainly binary: if any of the parameters exceeds the corresponding threshold, the epoch is marked as an artifact. As the signal energy distribution in the frequency or time domain varies strongly between subjects, we have chosen thresholds relative to the statistical properties of the considered signal. For example:

$$threshold = mean(EEG) + k * std(EEG)$$

where k is a factor of proportionality and *std* is the standard deviation.

The various procedures are the following (for more details, see *http://tcts.fpms.ac.be/publications/techreports/DEA_sd.pdf*):

P1. Cardiac interference detection and correction on EEG (Atf_cardE) and on EOG (Atf_cardO). The basis of the method for removing cardiac interference was presented in [8]. It is based on a modification of the independent component analysis algorithm which gives promising results while only using a single-channel EEG (or EOG) and the ECG.

P2. Slow ondulations detection and correction on EEG (Atf_ondE) and on EOG (Atf_ondO). Slow ondulation artifacts are generally due to breathing or sweating. Their frequencies are lower than those of the slowest waves of the sleep (rhythm delta). Therefore, their extraction can be realized by a simple filtering, with cut-off frequency adjusted to the smallest frequency of the delta band.

P3. Saturations detection on EEG (Atf_satE), on EOG (Atf_satO) and on EMG (Atf_satM). The basic idea of this procedure is to locate epochs where the EEG signal remains at its maximal value of saturation during a sufficient time.

P4. Unusual increase of EEG detection (Atf_highE). These artifacts can for example be caused by EOG interferences. If the amplitude of the EEG signal exceeds a first threshold for any of the epochs, the onset and the offset of the artifact are researched. These are defined as the instant after which the amplitude of the EEG becomes lower than a second threshold (lower than the first threshold). Then the corresponding epochs are marked as artifact epochs.

*P5. Failing electrode detection on EEG (Atf_noE) and on EOG (Atf_noO).*This procedure locates the relatively constant amplitude (near to zero) of the signals EEG or EOG. Such artifacts are sometimes obtained at the end of the nights when the electrodes are disconnected.

P6. Highlights abrupt transitions detection on EEG (Atf_transE). Highlights abrupt transitions such as spikes are identified by locating slopes above some threshold. Let

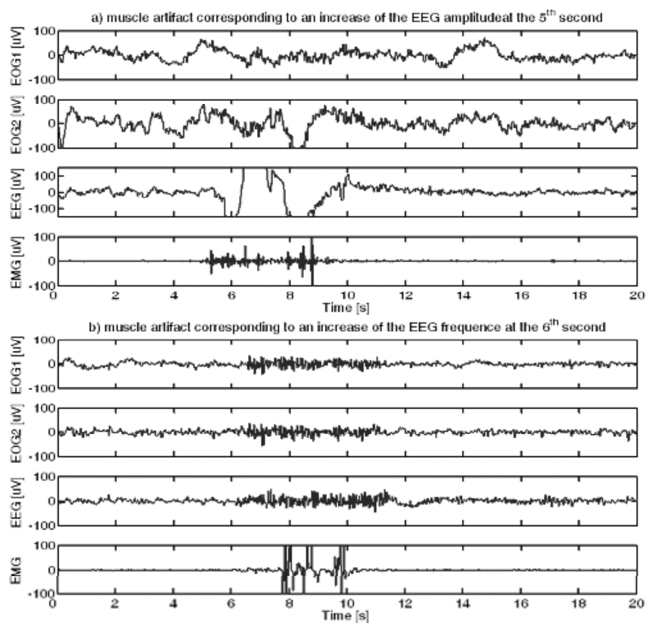

Fig. 1 Examples of muscle or movement artifacts

us note that epileptic spikes are not actually artifacts (since they have no artificial origin), but they can nonetheless obstruct the sleep stage classification. This is why we identified them as the artifacts.

P7. 50/60Hz mains interferences detection on EEG (Atf_50E). This interference network can easily be detected given the evident peak which takes place around 50Hz (or 60Hz) on the Fourier transform.

P8. Muscle or movement artifacts detection on EEG (Atf_mvtE). This algorithm detects temporary increase of muscular tone accompanied by disturbances on the EEG. These disturbances are of two types: they can be either a voltage increase as illustrated on Fig 1a. , or a change of rhythm of the EEG activity such as illustrated on Fig 1b.

P9. Detection of artifacts in EOG constituted of in-phase movements (Atf_phaseO). As the ocular movements are binocular and synchronous, the EOG recordings should appear in opposition of phase while placing electrodes on the lateral canthi and by using the same reference on the mastoid. The ocular artifacts are therefore easily identifiable since they correspond to in-phase movements of the EOG.

III. Results

A. Content of the artifact database

On the basis of the artifact scoring carried out by the expert, we first examined the content of the database in terms of short duration artifacts (Table 1).

Table 1 content of the artifact database based on the visual artifact scoring

Code	Type	Number of seconds	%
P3-a	Saturations of EEG (Atf_satE)	0	0
P3-b	Saturations of EOG (Atf_satO)	0	0
P3-c	Saturations of EMG (Atf_satM)	0	0
P4	Unusual increases of EEG (Atf_highE)	639,180	3,551
P5-a	Failing electrode on EEG (Atf_noE)	118,610	0,659
P5-b	Failing electrode on EOG (Atf_noO)	118,520	0,658
P6	Highlights abrupt transitions of EEG (Atf_transE)	46,790	0,260
P7	50/60Hz on EEG (Atf_50E)	23,980	0,133
P8	Muscle or movement artifacts on EEG (Atf_mvtE)	494,600	2,748
P9	artifacts in EOG (Atf_phaseO)	566,270	3,146
O-a	Other artifacts on EEG	129,73	0,72
O-b	Other artifacts on EOG	6,190	0,034
	All short artifacts on EEG	1014,930	5,639
	All short artifacts on EOG	690,980	3,839
	All short artifacts on EMG	0,000	0,000

The difference between the total duration of all short artifacts on EEG and the sum of durations of each type of artifact on this signal (P3-a+P4+P5a+P6+P7+P8) is due to the presence of multiple artifacts in some epochs.

As it can be seen, 5.64% of the total EEG recorded time contains artifacts. Among those, most frequent artifacts are "unusual increase of EEG" followed by "artifacts in EOG" and then "Muscle or movement artifacts".

No "saturation" artifact was found in the database. We therefore used other polysomnographic signals to tune the parameters of this procedure. These signals were not scored by the expert but simply examined visually by the authors.

B. Results of the minimization procedures

The ECG artifact removal procedure was previously tested on 10 excerpts of polysomnographic sleep recordings containing ECG artifacts and other typical artifacts [8]. It was shown that it is robust to various waveforms of cardiac interference and to the presence of other artifacts. Two hundred successive interference peaks of each of these excerpts were visually examined to compute the number of corrected peaks. We found a correction rate of 91.1%.

The removal of slow ondulations artifacts was only checked visually by the expert. It seems that the artifact can be well corrected without distorting the EEG, as it can be seen in Fig 2.

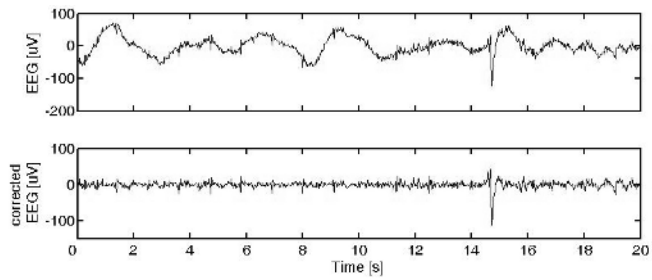

Fig. 2 Removal of slow ondulations artifacts on EEG

C. Results of the detection procedures

Concerning the short duration artifacts, the concordance between the expert scoring and the automatic detection procedures with the default thresholds, was examined as follows: 1) a true positive (TP) was counted when an artifact was automatically detected in an epoch also marked as an artifact by the expert, 2) a false positive (FP) when an artifact was automatically detected in an epoch classed as non-artifact by the expert, 3) a true negative (TN) when no artifact was detected neither automatically nor visually by the expert, 4) a false negative (FN) when no artifact was automatically detected in an epoch marked as artifact by the expert.

Then we computed the *agreement rate= (TP+TN)/(TP+TN+FP+FN)*, the *sensitivity=TP/(TP+FN)* and the *specificity=TN/(TN+FP).*

The results obtained for each detection procedure on the central EEG are exposed in Fig 3, as well as the global results of the detection of any artifacts on this EEG. The results corresponding to the EOGs and the EMG are shown on Fig 4. If an artifact is not present (according to the expert) in the training database, the sensitivity figure has no sense. That is why we indicated it by an asterisk (*).

As it can be seen, the procedures corresponding to the more frequent artifacts (i.e. unusual increase of EEG, artifacts in phase on EOG and Muscle artifacts) are unfortunately those which have the lowest sensitivities. However, as a whole, the results show an acceptable agreement between our package of software and the human scoring with agreement rates of 92.18%, 95.98% and 100% respectively on the EEG, EOG and EMG. Without making distinction between the various signals, these results correspond to a global agreement rate of 96.06%, a global sensitivity of 83.67% and a global specificity of 96.47%.

Finally, by varying the length of the analysis epoch from 1.25s to 1s, we observed that it introduced only little changes in the expert/software concordance (agreement rate = 96.46%, sensitivity = 82.33% and specificity =96.90%).

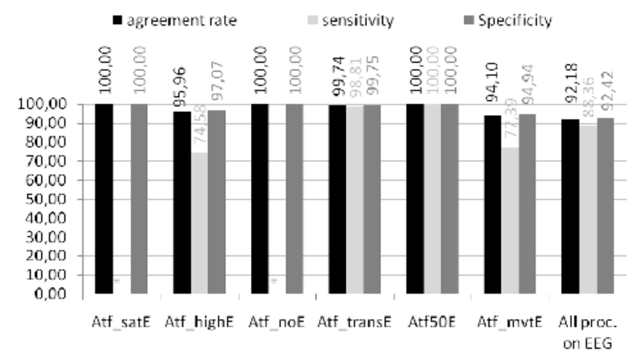

Fig. 3 Results of the detection procedure on the central EEG

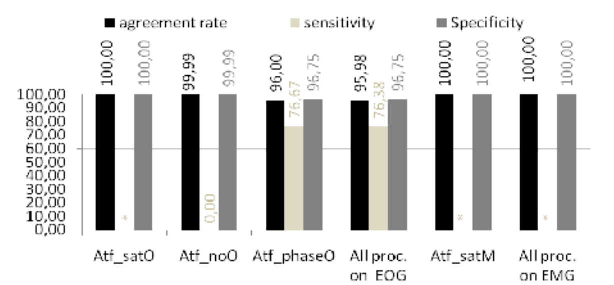

Fig. 4 Results of the detection procedure on the EEGs and on the EMG

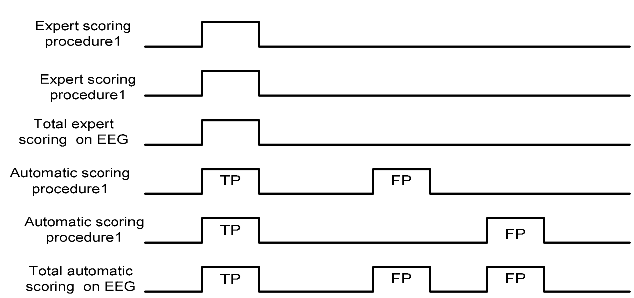

Fig. 5 Illustrative example of detection process

IV. Discussion

By looking at the Fig 3, one could be surprised of obtaining a total rate of agreement on the EEG of only 92.18% whereas each separate procedure has a higher agreement rate. Actually, this is due to the fact that false positives (FP) introduced by the various algorithms are not always located at the same place, while true positives (TP) are sometimes detected at the same epochs (fig 5). There is thus an increase in FP (proportionally to the number of TP) in the global detection on EEG. This explains why the total agreement rate is lower, while sensitivity is slightly modified and sensitivity is not affected. Fortunately, the number of epochs classified as non-artifact remains sufficient for feature extraction and sleep stage classification.

V. Conclusions

In conclusion, our findings showed that the proposed artifact minimization procedures and detection algorithms (although rather simple since they are mainly binary) are reliable in a context of classification in sleep stage classification. Indeed they give promising and repeatable results (agreement rate = 96.06%, sensitivity = 83.67% and specificity =96.47%) without requiring any human intervention.

The approach has however some limitations: (i) it is running on epochs of fixed length rather than locating the actual onset and offset of the artifacts. However using fixed length epochs dramatically simplifies the algorithm and the remaining part of signal is generally sufficient for the sleep stage classification. (ii) Although the parameters are calculated according to the statistical properties of the signal, their values (once determined) remain unchanged for all the duration of the recording. This can be can be inappropriate in sleep recording with fluctuation of tonicity level. The use of adaptive threshold rather than absolute threshold could then be investigated in future works.

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