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Artifact Processing in Computerized Analysis of Sleep EEG – A Review

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Sleep EEG analysis · Artifact minimization · Artifact identification

Abstract
Quantitative analysis of sleep EEG data can provide valuable additional information in sleep research. However, analysis of data contaminated by artifacts can lead to spurious results. Thus, the first step in realizing an automatic sleep analysis system is the implementation of a reliable and valid artifact processing strategy. This strategy should include: (1) high-quality recording techniques in order to minimize the occurrence of avoidable artifacts (e.g. technical artifacts); (2) artifact minimization procedures in order to minimize the loss of data by estimating the contribution of different artifacts in the EEG recordings, thus allowing the calculation of the 'corrected' EEG (e.g. ocular and ECG interference), and finally (3) artifact identification procedures in order to define epochs contaminated by remaining artifacts (e.g. movement and muscle artifacts). Therefore, after a short description of the types of artifacts in the sleep EEG and some typical examples obtained in different sleep stages, artifact minimization and identification procedures will be reviewed.

Introduction

In recent years, increasing efforts have been made to develop computer-assisted sleep analysis systems [for review see 1–3]. In 1993, a consensus report of the EC concerted action 'Methodology for analysis of the sleep-wakefulness continuum' was published by Kemp [4], recommending the use of a standard format for digitized polygraphic recordings (EDF-format, Kemp et al. [5]) and of a time resolution of 1 s for describing sleep/wake-related signal characteristics on a continuous scale. New approaches to the automatic analysis of human sleep were presented by Roberts and Tarassenko [6], Schaltenbrand et al. [7] and Pardey et al. [8]. Based on these previous results, a European project ('SIESTA – A new standard

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for integrating polygraphic sleep recordings into a comprehensive model of human sleep and its validation in sleep disorders') started in September 1997. This project, comprising 8 European sleep laboratories and 8 engineering departments as partners, aims at extensive novel research on the architecture of human sleep, as well as the development and evaluation of advanced methods for sleep analysis, based on polygraphic measurements, most prominently EEG. One of the objectives of SIESTA is the development of an enhanced computer-based system for polysomnographic analysis, which is reliable, reproducible, does not rely on rules to be interpreted by humans, describes sleep on a smaller temporal resolution and goes beyond the classical discrete stages [for more details on SIESTA including partner list and recording protocol see http://www.ai.univie.ac.at/siesta]. One requirement for achieving these ambitious goals is a reliable and valid artifact processing strategy, on the one hand minimizing the amount of data that have to be rejected, and on the other ensuring that the obtained results are not influenced by undetected artifacts.

Artifacts in the EEG can be defined as any potential difference due to an extracerebral source. The importance of dealing with artifacts effectively, both in visual and in quantitative EEG analysis, is unequivocally accepted, as artifacts can mimic almost any kind of EEG pattern [9, 10] and artifacts included in automatic analysis can seriously affect the results. Brunner et al. [11], for instance, demonstrated that rejection of short-lasting muscle bursts significantly reduced power spectral density in all frequencies from 0.25 to 32 Hz, most prominently of course in the faster frequency bands. Thus, the careful handling of artifacts is of utmost importance for EEG data processing, and reliability and validity of the artifact processing strategy used should be reported. Of course, artifacts themselves may contain valuable information. In sleep analysis for instance, eye movement and muscle artifacts in the EEG recordings might facilitate classification of sleep stages. Nevertheless, if the aim of the analysis is to quantify patterns of cerebral activity (e.g. sleep spindles, K-complexes) or to describe the behavior of the brain during sleep, only artifact-free epochs should be included in the analysis.

In addition to technical and movement artifacts, ocular, electromyographic (EMG), electrodermal, electrovascular and respiratory signals can interfere with the EEG as artifacts. The aim of the present paper is to briefly describe types of artifacts and to present an overview of procedures for artifact minimization and identification with special emphasis on the sleep EEG.

Types of Artifacts

Ocular artifacts either result from eye movements, which change the external electrical field of the cornea-retinal dipole, or from movements of the eyelids (blinks), which have a shunting effect on this field. While blink artifacts may only occur during the wake periods, slow and rapid eye movements (REM) can contaminate the sleep EEG. For EEGs recorded with symmetrical reference (e.g. versus the average of left and right mastoids), maximal interference due to vertical eye movements is found at frontopolar sites, with an exponential decrease towards occipital sites. Maximal interference due to horizontal eye movements is at frontotemporal sites, with opposite signs for the left and the right hemisphere and a linear slope between these two extremes [12].

EMG artifacts often appear in combination with swallowing or body movements. Muscle artifacts can range from single spikes separated from each other to a continuous interference, and from rather small to relatively large amplitudes. Brunner et al. [11] reported short-lasting muscle artifacts in the sleep EEG more frequently towards the end of non-REM sleep periods. EMG arousals were uniformly distributed within REM sleep, but concentrated at the beginning and the end of non-REM periods [13]. Moreover, Pilcher and Schulz [14] reported a close correspondence between transient EMG activity and changes in EEG activity.

Body and head movements may induce not only muscle artifacts but also slow potential shifts, which can be misinterpreted as delta activity [15]. The occurrence of body movements during sleep was shown to be related to the sleep cycle [16] and was found to decrease progressively from waking to stages 1, REM, 2, 3 and 4 [17].

The electrical field generated by the heart can directly interfere with the EEG. This ECG interference is dependent on the orientation of the electrical dipole of the heart and is seen in several leads simultaneously. Pulse artifacts, on the other hand, usually affect only one lead as they are due to pulsating scalp arteries lying directly under the electrode.

Electrodermal artifacts can originate from changes in the electrolyte concentration of the EEG electrodes due to sweat secreted from the sweat glands. Phasic electrodermal artifacts can occur upon sudden arousal from light sleep stages.

Chest movements due to respiration may induce movement of the head and thus of the electrodes against the pillow, resulting in rhythmic slow potential shifts in these electrodes.

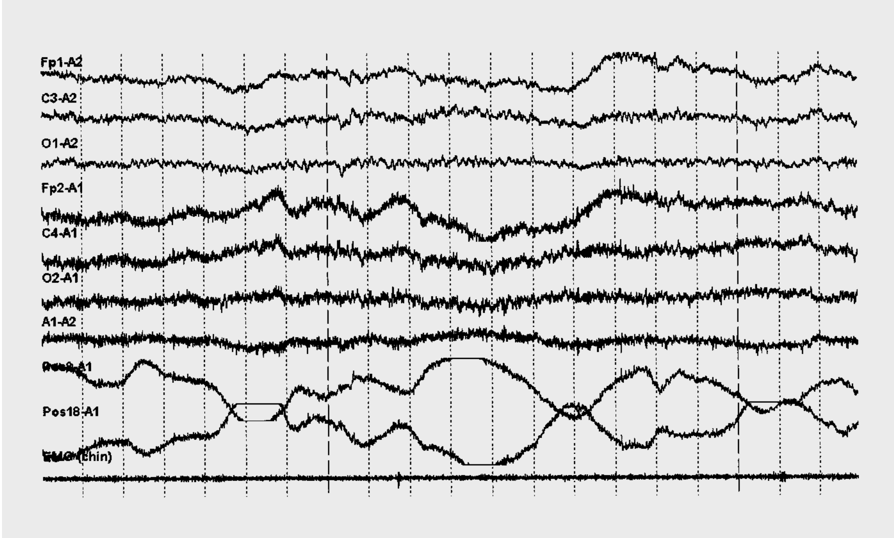

Fig. 1. Continuous muscle interference at electrode A1, and slow eye movement artifacts with maximal interference at frontopolar leads (stage 1).

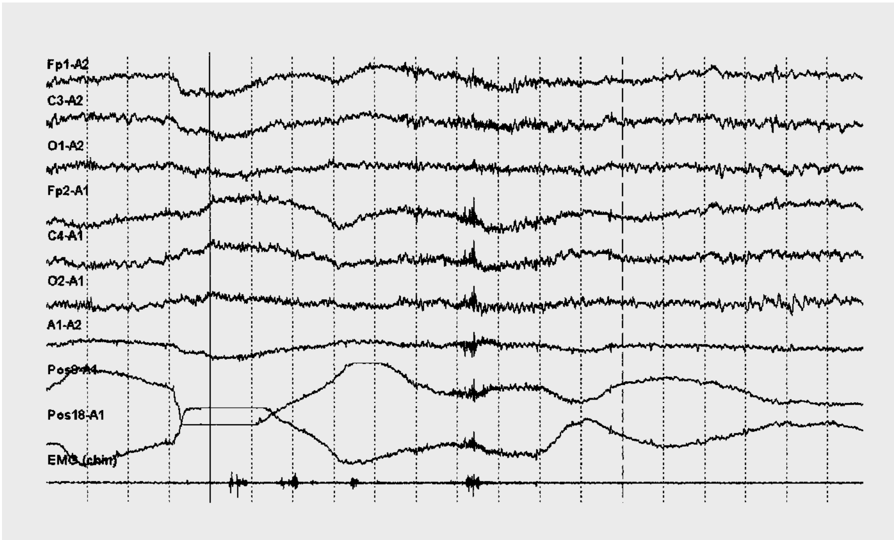

Fig. 2. Slow eye movements resulting in slow-wave EEG artifacts and, in the middle of the epoch, a muscle burst, resulting in high-frequency artifacts with maximal interference at A1 (stage 1).

Finally, technical artifacts may arise anywhere in the recording system, e.g. electrodes, leads or EEG instrument. Electrode artifacts may result from a sudden change in the direct current potential between the electrode and the skin, resulting in a sharp rise of variable amplitude and an exponential decay depending on the time constant used. Moreover, movement of the leads can electrostatically induce slow-wave artifacts. Thus, an appropriate environment for sleep recordings should include a high-quality and short wiring with shielding from electromagnetic fields.

Examples of 20-second polygraphic sleep recordings contaminated by various artifacts in different sleep stages are shown for a 41-year-old healthy female subject in figures 1–5: channels 1–3: electrodes at the left hemisphere referenced to right mastoid (Fp1, C3, O1-A2); channels 4–6: electrodes at the right hemisphere referenced to left mastoid (Fp2, C4, O2-A1); channel 7: left to right mastoids (A1-A2) for transformation into a symmetric reference; channels 8, 9: electrodes above left and below right outer canthus referenced to left mastoid (Pos8, Pos18-A1, according to Häkkinen et al. [18]; channel 10: submental EMG. EEG and EOG channels were recorded with a time constant of 1.56 s and a high-frequency filter of 75 Hz. For the EMG channel, a time constant of 0.0156 s was used. Note that the blocking of the EOG channels is not due to saturation of the amplifiers or the A/D converters but to display software.

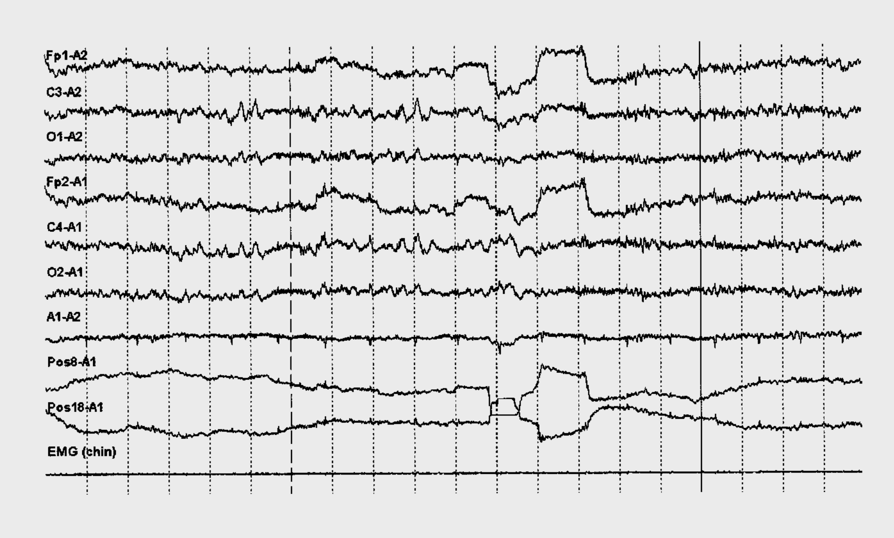

Fig. 3. ECG artifacts, best seen in A1-A2 due to the low-voltage background activity. Moreover, REM contaminate the EEG to a maximum at frontopolar leads (REM stage).

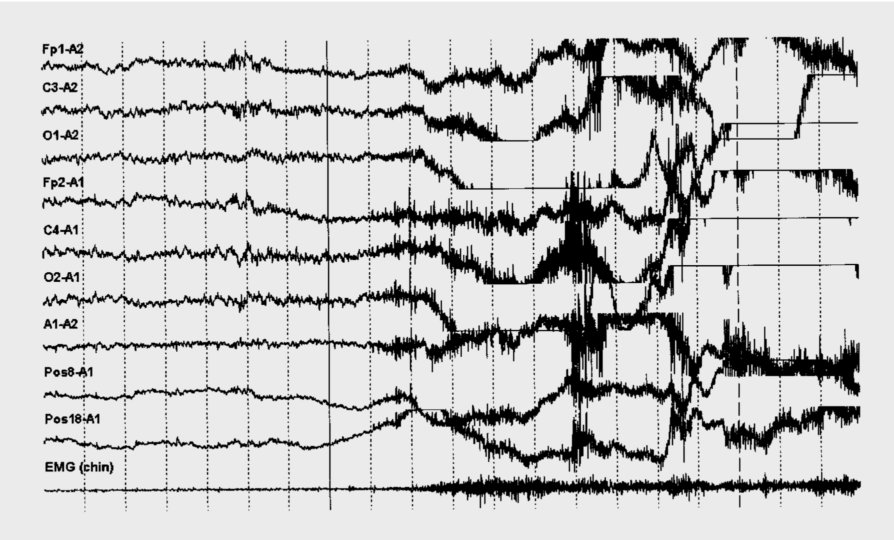

Fig. 4. Movement and muscle artifacts severely distort the EEG (movement time).

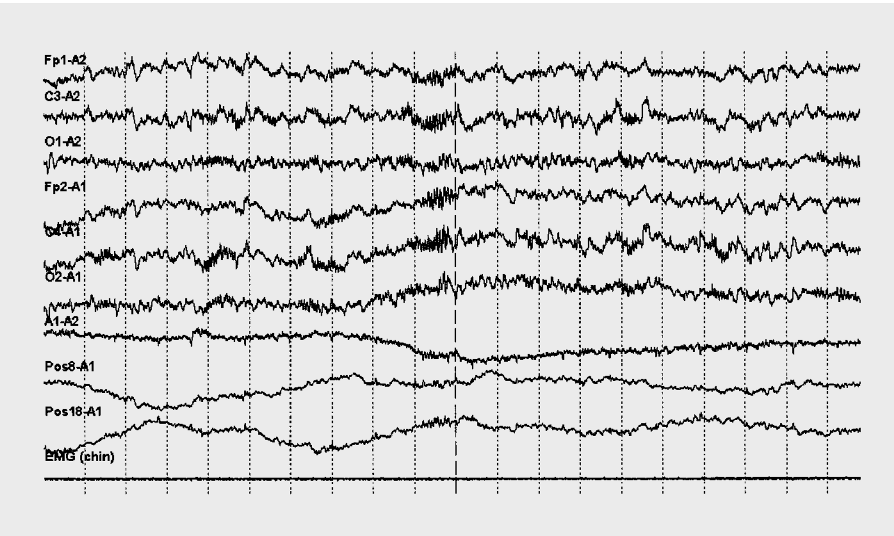

Fig. 5. An isolated slow electrode artifact can be seen at A1 (stage 2).

Artifact Processing

By far the best way of dealing with the problem of artifacts is to avoid their occurrence when recording the EEG. This goal can be achieved by using high-quality EEG recording techniques and an appropriate (cool and relaxing) environment. Furthermore, the electrodes should be applied with utmost care by an experienced EEG technologist, and electrode impedance should be tested before and after the sleep EEG recording. Moreover, sweat artifacts can be minimized by removing the outer layer of the skin under the electrode by skin drilling or rubbing the skin with abrasive paste [9]. Pulse artifacts can be avoided by replacing the electrode by a few millimeters. For unavoidable artifacts, artifact minimization is generally preferable to artifact rejection, since no loss of data is entailed. The artifact processing strategy to be used will depend on the data available (e.g. one- or multi-lead data), on the aim of the analysis (e.g. sleep staging or identification of sleep/wake-related EEG features) and on further data processing (e.g. ambiguity rejection).

Artifact Minimization

The aim of artifact minimization procedures is to extract artifacts from EEG epochs, so that the latter can be used in subsequent analysis. The elimination of all epochs contaminated by artifacts might result in an unacceptable loss of data (e.g. in REM stage at frontopolar leads). Artifact minimization procedures are available for artifacts whose original source can be recorded (e.g. by means of EOG for ocular artifacts or by means of ECG for cardiovascular artifacts) or whose original source can be reconstructed (e.g. by utilizing spatial information over time). Regardless of the method used, reliability (e.g. split-half reliability of regression factors or spatial components) and at least 'face' validity have to be checked for a representative sample.

Additional tests for validity may comprise residual variance or multiple correlation measures [19] and/or comparison of time-locked averages of raw and corrected EEG data (e.g. synchronized to the R-wave of the ECG). Moreover, all methods have to be carefully tested for possible distortion of the EEG waveforms.

Minimization Based on Digital Filters. Conventional low-pass filters (e.g. for reducing muscle artifacts) or high-pass filters (e.g. for reducing sweat artifacts) may severely distort both EEG and artifact signals. Several authors have shown examples how low-pass filtering of EEG epochs with muscle artifacts may cause them to closely resemble cerebral activity (most frequently beta activity, but also epileptic spikes [10, fig. 10]; or rhythmic activity in the alpha frequency band [9, fig. 9]. Larsen and Prinz [20] presented filter smoothers for seeking and correcting data outliers (such as ECG artifacts) based on an autoregressive model. In their computerized sleep scoring system, they used three filter operations with different autoregressive orders and different numbers of iteration to minimize statistical outliers due to spikes, ECG and muscle artifacts [21].

Minimization Based on Recorded Artifact Sources. These methods are based on the assumption that the original artifact sources can be recorded, and the 'measured' EEG is a linear combination of the 'true' EEG and these recorded artifact sources. Thus, the interference of the artifact in the EEG channel is determined, for example, by means of regression analysis in time [22] or frequency domain [23]. Next, the determined proportion of the artifact signal is subtracted from the 'measured' EEG. Obviously, these methods depend on the quality of the recorded artifact sources. EOG channels, for instance, also pick up prefrontal EEG activity [24]. Anderer et al. [12] discussed in detail problems that should be taken into account when using EOG minimization based on regression analysis. A comparison between several EOG minimization methods based on regression analysis in time and/or frequency domain can be found in Jervis et al. [25] and Brunia et al. [26]. Sahul et al. [27] presented an adaptive noise canceler for ECG artifact suppression in the sleep EEG, reporting slowly changing filter weights over the night. The authors compared ECG artifact minimization with fixed and varying filter weights, demonstrating that the ECG artifact in sleep EEG is indeed nonstationary.

Minimization Based on Reconstructed Artifact Sources. If topographic data are available, this spatial information can be utilized for the reconstruction of the original artifact sources. Berg and Scherg [28] presented a spatiotemporal multiple-source model for EOG artifact correction. In this model, ocular and cerebral activities are modeled by dipole sources. Mathematically equivalent to this approach is the signal-space projection method applied by Tesche et al. [29] to identify and remove eye blink artifacts. Lins et al. [30] used source components calculated by means of principal component analysis (PCA) of EEG and EOG recordings during ocular activity for removing eye artifacts from EEG data. An extension of these models without the need for a dipole model of the cerebral activity was introduced by Ille et al. [31]. This spatial component method for continuous artifact minimization is based on the spatial topography of artifacts derived by PCA and can be applied to any kind of artifact with adequately definable topographic distribution [32]. However, standard PCA results in uncorrelated and orthogonal components which are not necessarily independent, especially if the assumption of normal distribution has been violated. Independent component analysis (ICA), an extension of the PCA (which may be seen as subclass of ICA methods), is based on the assumption that brain and artifact activities are generated by independent processes (see Bell and Sejnowski [33] for discussions on the ICA methodology and Roberts [34] for a probabilistic approach). Recently, Vigário [35] applied this method in order to separate purely ocular activity in EEG and EOG channels from cerebral activity. The authors concluded that further research is required until the ICA method can be applied fully automatically. The major problems associated with current ICA methods are that there is no explicit noise process in the model, so noise is not removed, and that the method assumes signal stationarity. Good results may be obtained, however, with the method by using a small (quasi-stationary) sliding window on the signals.

Artifact Identification

The use of an automatic artifact identification method is essential to objectively exclude the influence of artifacts from the sleep EEG as visual artifact identification is a very time-consuming and monotonous task that is difficult to perform consistently. Automatic artifact identification can be achieved by either rejecting epochs contaminated by artifacts or by aggregating the information about the artifactual contamination to be integrated in subsequent analysis.

Identification Based on a Model for Artifacts. The simplest artifact model defines epochs with amplitudes surpassing a maximum voltage threshold (overflow check) as artifacts. A more sophisticated model defining different threshold values for amplitudes in different frequency bands has been implemented e.g. in the Medilog 9200 System (Oxford Medical Ltd.). Anderer et al. [12] described an automatic artifact identification method based on features obtained in time and frequency domain and empirically defined thresholds. An extended approach based on frequency and topographic properties (e.g. symmetry, extension) was presented recently by Nakamura et al. [36]. However, absolute artifact thresholds may be inappropriate in sleep recordings with fluctuation of tonic levels. Therefore Brunner et al. [11] used adaptive rather than absolute thresholds based on the moving median of a 3-min window for detection of muscle bursts.

Identification Based on a Model for Artifact-Free Data. One of the first models used to describe artifact-free EEG data was based on the assumption of Gaussian amplitude distribution in the undisturbed EEG. Ktonas et al. [37], for instance, defined departures from a normal amplitude distribution, evaluated by a χ^2 test, as artifacts in sleep EEG data. Already in 1977, Gevins et al. [38] described an artifact identification method based on departures from features calibrated from short visually evaluated artifact-free data segments. John et al. [39] extended this approach by using adaptive thresholds based on moving averages. Anderer et al. [40] implemented a similar approach based on three statistical variance measures (amplitude, slope and sharpness) in a commercial EEG mapping system.

Schaltenbrand et al. [7] used an unsupervised network (NeoART) to describe the artifact-free learning set by a union of hyperspheres. Any new data set not belonging to one of these prototypes is then excluded from further analysis (distance rejection). Moreover, the authors calculated an uncertainty index, with a high value of this index indicating that for this data set a unique decision cannot be made (uncertainty rejection). Another approach to reduce the influence of ambiguous data is to give a low weight to information, which resulted in low confidence at the output. This naturally gives rise to soft feature selection schemes, such as the automatic relevance determination of MacKay [41] and to methods based upon probabilistic graphical methods [42].

Discussion

So far, in most sleep laboratories, visual artifact rejection has been clinical routine. For instance, none of the clinical sleep laboratories involved in the SIESTA project applies fully automatic artifact processing. Even those partners using automatic sleep stages routinely have the sleep data checked for artifacts by an experienced sleep technologist. Therefore, reliable and valid automatic artifact processing strategies for sleep EEG data are urgently needed.

First, these strategies should apply artifact minimization whenever possible in order to minimize loss of data. For ECG artifacts, the original source can be recorded by means of ECG, and a linear model can be applied. However, as was shown by Sahul et al. [27], this interference is not time invariant and, thus, time-varying coefficients have to be considered (compare e.g. the ECG interference in A1-A2 in fig. 2, 3). In contrast to the ECG artifact source, the ocular artifact sources cannot be recorded solely, as EOG electrodes always pick up prefrontal EEG activity as well. Since the electrical field generated by the eyes decreases exponentially with the distance from the ocular dipole (Elbert et al. [43]), the best EOG to EEG ratio in the EOG channels is achieved when EOG electrodes are placed as close as possible to the eyes. Even though this demand is satisfied if electrode position 8 and 18 according to Häkkinen et al. [18] are used, two unipolar EOG leads are not sufficient to measure all the ocular variance. At least two orthogonal bipolar recordings (e.g. representing vertical and horizontal eye movements) are necessary [25]. Unfortunately, conventional sleep montages record eye electrodes referenced to mastoids and thus only one bipolar EOG channel is available. This means that different eye movements might result in the same deflection in the EOG channels, but in different ocular artifact interferences in the EEG channels (compare the out-of-phase deflections in the EEG channels for left and right hemisphere for the slow eye movements in fig. 2 with the in-phase deflections in the EEG channels for the rapid eye movements in fig. 3). Therefore, ocular artifacts cannot be corrected by a linear subtraction method based on one EOG channel. However, as multichannel recording devices are becoming more and more popular also in sleep medicine, information on spatial distribution can be utilized. Thus, following the above example, even if different eye movements might result in the same deflection in the EOG channels, they can be differentiated on the basis of their distribution across the scalp. Spatial component methods (e.g. PCA by singular value decomposition) can take advantage of this behavior [32]. By selecting epochs with high-amplitude eye movements (for a comparison between different eye movement detection algorithms see Värri et al. [44]), the spatial topography of the artifact can be described by its major spatial component, i.e. the eigenvector with the maximum eigenvalue [31]. Moreover, new approaches such as the ICA for source assessment and separation will be tested for their applicability in sleep EEG data [34, 45].

The remaining artifacts can be detected either by selecting (known) features of artifacts, or by building a 'rich' model of artifact-free EEG and then screening any unknown segment against it ('novelty detection') [46]. For each 1-second epoch and each EEG channel, an output function should indicate the probability for the occurrence of an artifact. Of course, longer time epochs are necessary to detect these slow-changing artifacts, but the probability for their occurrence can be given for each 1-second time window. In addition to EEG, EOG and ECG channels, respiratory channels should also be included in the model (e.g. for differentiating between sweat and respiration-related slow-wave artifacts). A final decision whether this EEG period can be included in the analysis will depend on the sensitivity of the processing method to the specific artifact (e.g. sweat artifacts will not influence spindle detectors) and the aim of the analysis. That means while for single-lead analysis, all artifact-free data per channel can be utilized, for topographic analysis (e.g. hemisphere differences or frontooccipital gradients as reported recently by Werth et al. [47]), all EEG channels within one epoch have to be free of artifacts.

A large sample of normal subjects across all age groups and of patients suffering from sleep disturbances should be available for selecting representative and independent samples of artifacts for developing and for testing/validating the automatic artifact processing method. Based on these data, the procedure can be optimized to reject only those epochs disturbed by artifacts that might affect the results, so that as much data as possible can be used for subsequent analysis. Furthermore, analysis on multichannel data using a Bayesian approach that takes confidence intervals on extracted features into account might promise satisfying results, even if not all artifacts can be completely minimized or identified.

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