Real-Time Subspace Denoising of Polysomnographic Data

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ABSTRACT

Analysis of polysomnographic (PSG) biosignals, collected during sleep studies, is the current gold-standard for sleep disorder assessment. Motion and imperfect contact of the wired sensors attached to the human body, to acquire the data, can introduce noise and artifacts that can diminish the quality of the collected data. In this work we present a subspace denoising method that exploits the low-dimensionality of the acquired data, and is able to reduce the noise and increase the SNR ratio in real-time, resulting in improved data quality.

Categories and Subject Descriptors

C.3 [**Special-purpose and Application-based Systems**]: Signal processing systems; I.5.4 [**Pattern Recognition**]: Applications —*Signal processing*

General Terms

Theory, Measurement, Reliability.

Keywords

Denoising, polysomnography, signal, real-time, sleep study.

1. INTRODUCTION

Sleep studies are standardized tests that record body activity during sleep, in order to assess the existence of a sleep disorder, in patients with sleep problems. A sleep disorder, or somnipathy, is a medical disorder of the sleep patterns that, if left untreated, can lead to sleep deprivation. Sleep deprivation, in turn, can lead to traffic accidents, work injuries, increased risk of heart disease, heart attack, high blood pressure, stroke, diabetes, and death. Sleep disorders, according to [10] can also cause mental disorders, like depression. The *International Classification of Sleep Disorders: Diagnosis and Coding Manual*, second edition (ICSD-2) lists more than 80 sleep disorders [8]. The vast majority of these disorders are classified in the following six categories: *a*) Insomnias *b*) Sleep-related breathing disorders *c*) Hypersonmias of central origin *d*) Circadian rhythm disorders *e*) Parasomnias *f*) Sleep-related movement disorders.

Polysomnography (PSG) [4] and Actigraphy are the most common tests used to identify sleep disorders, with PSG being the gold standard used by sleep experts, as the most reliable sleep study method available. PSG is the measurement of multiple physiologic parameters of the human body during sleep, including brain activity (EEG), eye movements (EOG), muscle activity or skeletal muscle activation (EMG) and heart rhythm (ECG), breathing and oxygen levels, among others. To measure those parameters, a polysomnogram will typically record a set of signal channels requiring multiple wire attachments to the patient. Imperfect contact, patient movements during sleep, and other factors, can introduce noise and artifacts to the recorded signals, thus diminishing the quality of the data collected for sleep disorder assessment.

In this work, we introduce a method for noise reduction in data recorded through PSG studies, aiming to increase the reliability of the sleep disorder assessment results. Our method is able to track a low-dimensional subspace that accurately models the acquired data vectors $\mathbf{x}_t$, and subsequently project the data onto this low-dimensional subspace to remove noise. The low-dimensional signal subspace used to model the PSG data is tracked by relying on the projection approximation subspace tracking scheme, originally proposed in [11]. The PSG data are then projected on the estimated signal subspace leading to a real-time noise power reduction.

Previous efforts on PSG signal denoising, have attempted to denoise individual signals in isolation. For example, Estrada et.al. [2], introduce wavelet-based EEG denoising for automatic sleep stage classification. Sanemi et.al. [9], use nonlinear Bayesian filtering to denoise ECG signals, while more recently, Mert et.al. [6], denoise EOG signals using empirical mode decomposition and detrended fluctuation analysis. Looney et.al. [5], as in our approach rely on subspace estimation to perform subspace denoising of EEG artifacts via multivariate EMD. However, the proposed method in [5] is an offline technique in the sense that does not treat the data as a constant stream of information with time-varying statistics. Our method takes advantage of the complementary information obtained by multiple PSG channels,

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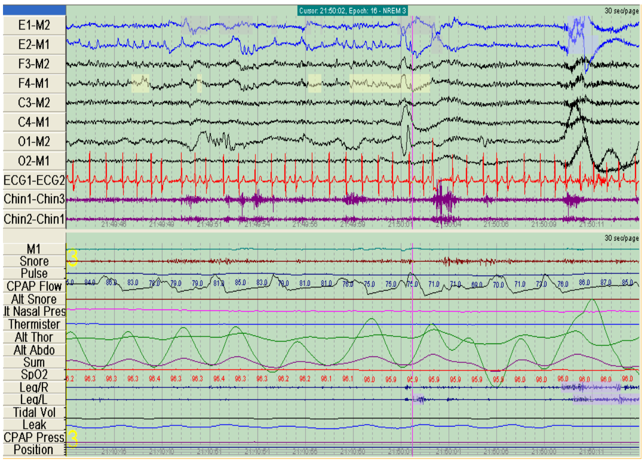

Figure 1: A 30-second epoch visualization of the signals recorded by Profusion PSG 3 software.

to achieve fast and reliable data denoising in real-time, while tracking in real-time a low-dimensional model that can be used to describe the PSG data.

The remaining of this paper is organized as follows. Section 2 provides an overview of the PSG data used in our experiments. In section 3, we develop the theoretical model of our noise reduction method and denoising approach. Section 4 illustrates our experimental findings, by applying denoising to PSG data recorded from real patients. Finally, in section 5 we discuss our concluding remarks.

2. PSG DATA DESCRIPTION

The data used in our experiments were collected during sleep study sessions, at the Texas State Sleep Center, using the Compumedics®Profusion PSG 3 software. Profusion PSG allows the recording of 28 different physiological signals, at different sampling rates, as listed in Table 1. Signals #1-8 are electroencephalogram (EEG) signals, signal #9 is the electrocardiogram (ECG) (combination of two electrodes), signals #10 & 11 are electromyography (EMG) signals from the chin, signal 12 is a mastoid region reference signal, signals #13 & 16 monitor snoring, and signals #23 & 24 are EMG signals from the legs. All the above signals are sampled at 128 Hz. For simplicity, in our experimental evaluation, we only apply our denoising method to signals sampled at this frequency.

Profusion PSG, besides facilitating signal recording and exporting into textual format for analysis, provides visualization of the raw signals, for visual assessment by the clinical expert. Signal denoising can benefit both the human expert, in their visual assessment, and possible machine-based analysis methods for the detection of events of interest. In fact, Profusion PSG provides some basic functionality for automatically detecting events like sleep stage, limb movement, respiratory events, etc. Figure 1 shows a snapshot of a 30-second epoch, of a patient in NREM 3 sleep stage, as recorded in a sleep study.

3. REAL-TIME SUBSPACE DENOISING

Next, we exploit the low-dimensionality of the acquired sleeping data contained in the $N \times 1$ vector $\mathbf{x}_t$ at time instant t for $t = 0, 1, 2, \ldots$. Here $N = 16$ and contains all the measurements acquired at time instant t from all data streams sampled at 128Hz. Specifically, the goal is to track a low-dimensional subspace that accurately models the acquired data vectors $\mathbf{x}_t$, and subsequently project the data onto this low-dimensional subspace to remove noise in real-time and improve the sensing signal-to-noise (SNR) ratio. It should be emphasized that denoising is a necessary preprocessing step to improve overall quality of the acquired data and improve the performance of any subsequent data mining tasks.

Table 1: Signals recorded by Profusion PSG.

Signal #	Signal type	Sampling freq.
1	E1-M2	128 Hz
2	E2-M1	128 Hz
3	F3-M2	128 Hz
4	F4-M1	128 Hz
5	C3-M2	128 Hz
6	C4-M1	128 Hz
7	O1-M2	128 Hz
8	O2-M1	128 Hz
9	ECG1-ECG2	128 Hz
10	Chin1-Chin3	128 Hz
11	Chin2-Chin1	128 Hz
12	M1	128 Hz
13	Snore	128 Hz
14	Pulse	16 Hz
15	CPAP Flow	16 Hz
16	Alt Snore	128 Hz
17	Alt Nasal Press	16 Hz
18	Thermister	32 Hz
19	Alt Thor	32 Hz
20	Alt Abdo	32 Hz
21	Sum	32 Hz
22	SpO2	16 Hz
23	Leg/R	128 Hz
24	Leg/L	128 Hz
25	Tidal Vol	16 Hz
26	Leak	16 Hz
27	CPAP Press	64 Hz
28	Position	16 Hz

3.1 Noisy Low-Dimensional Signal Model

We consider the noisy data $\mathbf{x}_t^n := [x_1^n[t], \ldots, x_N^n[t]]^T$ which model the presence of noise in the acquired sleeping data via the following additive noise model

$$\mathbf{x}_t^n = \mathbf{x}_t + \mathbf{w}_t, \tag{1}$$

where $\mathbf{w}_t := [w_1[t], \ldots, w_N[t]]^T$ contains the sensing noise, while $\mathbf{x}_t$ corresponds to the informative part that we are interested in recovering and it is assumed to be uncorrelated with the noise vector $\mathbf{w}_t$. Next, a linear low-dimensional model is used to represent the informative part $\mathbf{x}_t$ in (1). In detail, the informative part $\mathbf{x}_t$ of the sensor data is modeled as

$$\mathbf{x}_t = \mathbf{H}_t \mathbf{s}_t, \tag{2}$$

where $\mathbf{H}_t$ is a $N \times r$ matrix which denotes the time-varying linear subspace on which the information part is assumed to lie, whereas the $r \times 1$ vectors $\mathbf{s}_t$ corresponds to corresponding projection coefficients (or principal components, see e.g.,

[1]).

The time-varying matrix $\mathbf{H}_t$ can be interpreted as a linear subspace approximation of the informative signal acquired in $\mathbf{x}_t$ and observed via the noisy vectors $\mathbf{x}_t^n$. Define $\mathbf{H}_t := [\mathbf{h}_{1,t} \ldots \mathbf{h}_{r,t}] \in \mathbb{R}^{N\times r}$ and let $\mathbf{\Sigma}_{s,t}$ be the diagonal covariance matrix of the uncorrelated principal components in $\mathbf{s}_t$. Then, then the covariance matrix $\mathbf{\Sigma}_{x^n}$ of the noisy data $\mathbf{x}_t^n$ can be written as

$$\mathbf{\Sigma}_{x,t}^n = \mathbb{E}[\mathbf{x}_t^n(\mathbf{x}_t^n)^T] = \mathbf{H}_t\mathbf{\Sigma}_{s,t}\mathbf{H}_t^T + \sigma_w^2\mathbf{I}_{N\times N}, \qquad (3)$$

where $\mathbb{E}[\cdot]$ denotes the expectation operator and σ_w^2 denotes the noise variance at each data stream. Further, the covariance $\mathbf{\Sigma}_{x,t} := \mathbf{H}_t\mathbf{\Sigma}_{s,t}\mathbf{H}_t^T$ has rank r which implies that it has r nonzero eigenvalues, while the corresponding r principal eigenvectors form the r-dimensional signal subspace $\mathbf{H}_t$.

3.2 Low-Rank Projection-Based Denoising

The low-dimensionality of $\mathbf{x}_t$ is employed to reduce the noise power in $\mathbf{x}_t^n$ by projecting the latter vectors onto the signal subspace spanned by the columns of $\mathbf{H}_t$. Specifically, let the singular value decomposition of $\mathbf{H}_t$ be $\mathbf{H}_t = \mathbf{U}_{h,t}\mathbf{S}_{h,t}\mathbf{V}_{h,t}^T$, where $\mathbf{S}_{h,t} \in \mathbb{R}^{r\times r}$ is diagonal and $\mathbf{U}_{h,t} \in \mathbb{R}^{N\times r}$ and $\mathbf{V}_{h,t} \in \mathbb{R}^{r\times r}$ orthonormal matrices. Then, matrix $\mathbf{U}_{h,t}$ contains the r principal eigenvectors of $\mathbf{\Sigma}_{x,t}$, thus projecting the data $\mathbf{x}_t^n$ onto $\mathbf{U}_{h,t}$ results

$$\mathbf{x}_t^p := \mathbf{U}_{h,t}\mathbf{U}_{h,t}^T\mathbf{x}_t^n = \mathbf{H}_t\mathbf{s}_t + \mathbf{U}_{h,t}\mathbf{U}_{h,t}^T\mathbf{w}_t. \qquad (4)$$

Note that the low-dimensional signal part $\mathbf{H}_t\mathbf{s}_t$ in $\mathbf{x}_t^p$ remains intact and the same as in $\mathbf{x}_t^n$ after projection. However, the total noise variance of the projected noise $\mathbf{U}_{h,t}\mathbf{U}_{h,t}^T\mathbf{w}_t$ can be found readily to be $r\sigma_w^2$, which is smaller than the total noise variance before data projection, namely $N\sigma_w^2$. Thus, the overall effect of the noise is reduced on the projected data in (4). Thus, the projected data vectors $\mathbf{x}_t^p$ are characterized by a larger signal-to-noise ratio (SNR) compared to the original noisy data vectors $\mathbf{x}_t^n$.

The idea of projection-based denoising is not new and it has been effectively applied in image denoising, see e.g., [7] and [3]. However, to the best of our knowledge it has not been utilized in denoising PSG data streams which are extremely heterogeneous. Effective application of the projection-based denoising in (4) requires knowledge of the time-varying signal eigenspace $\mathbf{U}_{h,t}$. To this end, a real-time process known as projection approximation subspace tracking (PAST), see e.g., [11], will be employed to estimate the low-rank signal eigenspace using the data $\mathbf{x}_t^n$.

3.3 Online Subspace Tracking

The PAST scheme, originally proposed in [11], is an iterative approach to minimize in an online fashion the exponentially weighted mean-square error

$$\hat{\mathbf{C}}_t := \arg\min_{\mathbf{C}} \sum_{\tau=0}^{t} \beta^{t-\tau}\|\mathbf{x}_\tau - \mathbf{C}\mathbf{C}^T\mathbf{x}_\tau\|_F^2 \qquad (5)$$

where $\beta \in (0,1]$ is a forgetting coefficient giving more emphasis to the recent data, while gradually forgetting the old data while $\mathbf{C}$ is a $r\times N$ matrix. As demonstrated in [11] the matrix $\hat{\mathbf{C}}_t$ can be used as an estimate for the signal eigenspace $\mathbf{U}_{h,t}$.

The PAST algorithm involves the following updating formulas at time instant t:

$$\begin{aligned}
\mathbf{y}_t &= \hat{\mathbf{C}}_{t-1}\mathbf{x}_t^n & (6)\\
\mathbf{m}_t &= \mathbf{P}_{t-1}\mathbf{y}_t & (7)\\
\mathbf{g}_t &= (\beta + \mathbf{y}_t^T\mathbf{m}_t)^{-1}\mathbf{m}_t & (8)\\
\mathbf{e}_t &= \mathbf{x}_t^n - \hat{\mathbf{C}}_{t-1}\mathbf{y}_t & (9)\\
\hat{\mathbf{C}}_t &= \hat{\mathbf{C}}_{t-1} + \mathbf{e}_t\mathbf{g}_t^T & (10)
\end{aligned}$$

which are carried out at every time instant t and after a new data vector $\mathbf{x}_t^n$ has been acquired. The 'covariance' matrix $\mathbf{P}_t$ is initialized such that $\mathbf{P}_0 = \mathbf{I}_{r\times r}$, while the eigenspace estimate is initialized such that $\hat{\mathbf{C}}_t$

4. NUMERICAL TESTS

The denoising technique is tested in 16×1 data vectors that contain noisy PSG signals. Here we group 16 among the 28 PSG signals whose common characteristic is their sampling rate at 128Hz (see Table 1 for a complete list of all data streams).

The performance metric considered here will be the ratio of the noise power in the projected data over the noise power in the original data. Specifically, at time instant t the following *noise-reduction* ratio is calculated (in dB)

$$NR_t(dB) := 10\cdot\log_{10}\frac{\|\mathbf{x}_t^n - \mathbf{x}_t\|_2^2}{\|\mathbf{x}_t^p - \mathbf{x}_t\|_2^2}. \qquad (11)$$

If NR_t is positive this implies that the noise power is reduced in the projected data, whereas if it is negative it means that the noise power is amplified. We apply next the denoising procedure in 4000 data vectors acquired within a time interval of 31.25 seconds. Figures 2 and 3 display the histogram of NR_t values for all 4000 data vectors for a sensing SNR of 2dB and 8dB, respectively. In other words, it is displayed how many data vectors are associated with a given NR_t range of values. When the sensing SNR is 2dB (original data) the average of NR_t is 5.84dB which is a significant reduction is noise power, while the percentage of data vectors with a negative NR_t can be found to be only 3.5%. This is done by setting the signal subspace dimension to $r = 2$. Similarly, when the sensing SNR in the original data vectors is 8dB as can be found by the histogram in Fig. 3 the average of NR_t is 3.73dB, while the percentage of data vectors with a negative NR_t can be found to be only 1%. This is done by setting the signal subspace dimension to $r = 4$. Thus, the denoising of the PSG data is evident. One thing to notice is that as the sensing SNR in the original data goes up the average NR_t decreases. This happens due to the fact that as the sensing SNR goes up there is less noise to remove leading to a decrease in the NR_t values observed.

Table 2 depicts for different sensing SNR values (and corresponding low-dimension r) the mean NR achieved by the denoising method, as well the probability of having a negative NR_t, namely the outage probability $Pr[NR_t < 0dB]$, across the tested 4000 data vectors. These quantities are calculated running the denoising method for 40 independent Monte Carlo trials. The average NR in all different cases is positive and as the sensing SNR decreases the mean NR is increasing. As the sensing noise power decreases the NR achieved by denoising is decreasing since the noise present in the data is already decreasing. Also, it is worth mentioning that the outage probability is pretty small and does not

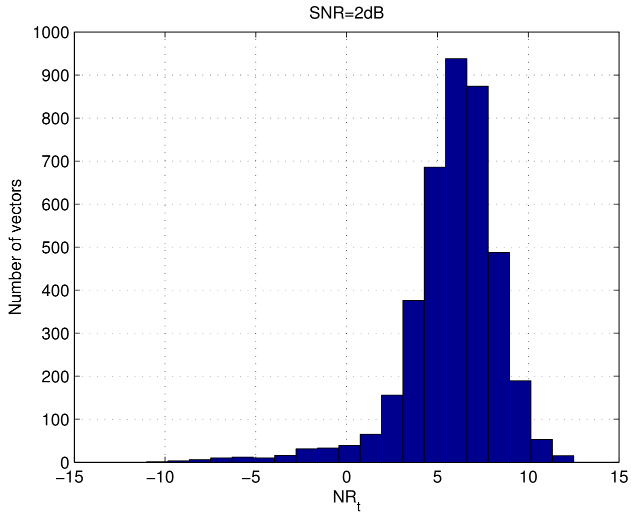

Figure 2: Histogram of NR_t values for a setting where the sensing SNR of the noisy data is 2dB.

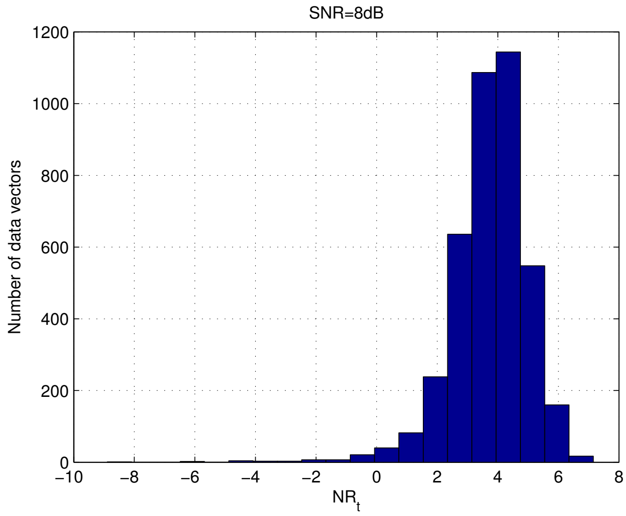

Figure 3: Histogram of NR_t values for a setting where the sensing SNR of the noisy data is 8dB.

Table 2: Mean noise-reduction and outage probability.

Sensing SNR (dB)	r	Mean NR (dB)	$Pr[NR_t < 0dB]$
0	2	6.40	0.02
2	2	5.84	0.03
4	2	5.10	0.04
6	4	4.09	0.02
8	4	3.73	0.01
12	4	2.45	0.05

exceed 5% in all different testing cases, which further implies that 95% of the time the real-time denoising method in fact reduces the noise power and improves the quality of the projected data vectors $\mathbf{x}_t^p$ that can be used for further processing such as classification and feature extraction.

5. CONCLUDING REMARKS

This work focused on carrying out denoising of polysomnographic data in real-time. A time-varying low-dimensional subspace model is utilized to model the informative part of the data which can be further used to reduce noise power. Projection of the data onto the low-dimensional signal subspace is utilized here to increase the SNR and improve the quality of the acquired PSG data. The low-dimensional subspace is tracked in real-time, while numerical tests demonstrate the capability of the proposed framework to reduce noise power.

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