

SLEEP STAGE CLASSIFICATION USING SPARSE RATIONAL DECOMPOSITION OF SINGLE CHANNEL EEG RECORDS

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ABSTRACT

A sparse representation of 1D signals is proposed based on time-frequency analysis using Generalized Rational Discrete Short Time Fourier Transform (RDSTFT). First, the signal is decomposed into a set of frequency sub-bands using poles and coefficients of the RDSTFT spectra. Then, the sparsity is obtained by applying the Basis Pursuit (BP) algorithm on these frequency sub-bands. Finally, the total energy of each sub-band was used to extract features for offline patient-specific sleep stage classification of single channel EEG records. In classification of over 670 hours sleep Electroencephalography of 39 subjects, the overall accuracy of 92.50% on the test set is achieved using random forests (RF) classifier trained on 25% of each sleep record. A comparison with the results of other state-of-art methods demonstrates the effectiveness of the proposed sparse decomposition method in EEG signal analysis.

Index Terms— Sleep stage classification, sleep-EDF, sparsity, rational functions, basis pursuit.

1. INTRODUCTION

Sleep deprivation or several sleep disorders such as insomnia and sleep apnea can cause disruption of normal daytime activities [1]. One of the main objective measure for sleep stage classification is the so-called polysomnogram (PSG) which contains biological signals of non-intrusive sensors such as electroencephalogram (EEG), electrooculogram (EOG), and electromyogram (EMG). The clinical diagnosis of sleep staging is currently performed using the universal standard developed by Rechtschaffen and Kales (R&K) [2]. Basically, it provides six distinct sleep stages: awake, four different non-rapid (NREM) and one rapid eye movement (REM) where the latter is associated with dreaming. Each sleep stage can be characterized by a specific EEG activity. For instance, the dominant EEG activities are discharges and spikes in stage I (drowsiness), K-complexes in stage II (light sleep) and delta waves in stages III and IV (deep/very deep sleep).

Generally, sleep quality assessment is usually performed

manually by medical experts. In order to improve the diagnosis several automated sleep classification systems have been proposed over the last decade. Many of these algorithms utilize time-frequency analysis of the EEG signal to extract discriminative features for sleep scoring. Decomposition of sleep EEG signal into primary frequency sub-bands via 8 levels Wavelet transform (WT) was first introduced in [3]. In this case, 13 features are extracted based on the energy of each sub-band which was used to train a feed forward artificial neural network (ANN) using back-propagation algorithm. Another decomposition technique was proposed in [4] based on the Hilbert-Huang Transform (HHT) which uses Empirical Mode Decomposition (EMD) to decompose the EEG signal into 7 sub-bands. Similarly, features were extracted based on the energy of the sub-bands.

In [5], we showed that one can improve the seizure classification accuracy of the classical DSTFT methods by representing the EEG with only a few rational functions. The reconstruction error was minimized via hyperbolic particle swarm optimization (HPSO) [6] which results in an optimal pole a_0 . Note that the classical DSTFT uses trigonometric basis without any free parameters. In case of RDSTFT the base functions are specific rational functions Φ_k that can be adapted to the signal via HPSO. Moreover, the MT rational system possesses the advantages of the classical DSTFT [5], such as orthogonality, FFT implementation and the perfect reconstruction is also possible [7]. In our former work [5], we considered only binary classification of epileptic seizures. In this study, we instead use RDSTFT to perform sleep stage classification, which is a more complex problem. Additionally, in order to increase the efficiency of the basic RDSTFT, we introduce a signal decomposition technique based on the MT rational system. In this method, an input signal is decomposed into multiple frequency sub-bands. For this purpose, MT rational coefficients of the signal are divided into non-overlapping subsets. Each frequency sub-band is then constructed using only one sub-set of the coefficients. Furthermore, in order to obtain the most compact representation of the sub-bands in time domain, the Basis Pursuit (BP) algorithm [8] is utilized to induce the sparsity on the proposed decomposition technique, which can provide more discrimi-

natory power for low-level features. Here, the feature vector is constructed by using the total energy of each sparse frequency sub-band. The performance of the proposed method is evaluated using 39 subjects of Sleep-EDF dataset [9]. A comparative study with the results of other state-of-art methods reported in the literature for the same classification problem and the same dataset, shows that the proposed method outperforms them with the overall accuracy of 92.50% and the overall F-1 score of 92.39% on the test set using Random Forest (RF) classifier trained individually on the 25% of each sleep record.

The rest of the paper is organized as follows. Section 2 briefly summarizes the related work on the RDSTFT spectra. Then, Section 3 introduces the sparse RDSTFT decomposition. Section 4 describes the sleep staging problem and the dataset, it discusses the experimental results as well. Finally, Section 5 concludes the paper.

2. RELATED WORK

In our former work [5], the Generalized Rational Discrete Short Time Fourier Transform was proposed using different types of rational orthogonal basis functions: ϕ_k where $0 \leq k \leq N - 1$ and N is the number of coefficients. In fact, similar to a windowed Fourier transform, the rational DSTFT of the signal f can be defined as:

$$\mathcal{R}_{\phi} \mathcal{F}_g f[n, k] = \sum_{m=0}^{M-1} f[n-m]g[m]\phi_k[m], \quad (1)$$

where $\phi_k[m] = \Phi_k(e^{-2\pi \frac{m}{M}})$ is a specific type of rational basis, $g[m]$ is a window function with length M . Based on the functions Φ , different rational systems can be introduced. Now, let us consider the sequence of inverse poles a_0, \dots, a_{N-1} which lie inside the open unit disk \mathbb{D} . Then, the so-called Malmquist–Takenaka (MT) system can be defined as:

$$\Phi_k(z) = \frac{\sqrt{1 - |a_k|^2}}{1 - \bar{a}_k z} \prod_{j=0}^{k-1} B_{a_j}(z),$$

with $0 \leq k \leq N - 1$, where $B_a(z)$ is a Blaschke function:

$$B_a(z) := \frac{z - a}{1 - \bar{a}z} \quad (z \in \mathbb{C} \setminus \{1/\bar{a}\}).$$

Note that, in our model we used only one pole a_0 with multiplicity $m_0 = N$. Namely, $a_0 = a_1 = \dots = a_{N-1}$. Furthermore, the flexibility of the rational DSTFT is due to the fact that the location of the pole $a_0 \in \mathbb{D}$ and the number of its multiplicity N , can be estimated according to the shape of the input signal. On one hand, perfect reconstruction requires $N = M$ and the non-uniform discretization of

the signal [7]. On the other hand, the inverse transform of the rational DSTFT for $N < M$ can be approximated as

$$f[n-m] \approx \frac{1}{g[m]} \sum_{k=0}^{N-1} \mathcal{R}_{\phi} \mathcal{F}_g f[n, k] \phi_k[m]. \quad (2)$$

3. SPARSE RATIONAL DSTFT DECOMPOSITION

3.1. Decomposition of EEGs using rational components

In the previous section, the EEG signal f is divided into shorter segments which are represented by a number of poles a_j and coefficients c_k^n in the MT rational DSTFT sense, i.e. $c_k^n := \mathcal{R}_{\phi} \mathcal{F}_g f[n, k]$. Furthermore, the m th sample of the n th segment $f[n-m]$ can be approximated by using Eq. (2). Each coefficient of the RDSTFT spectra points out to a specific frequency range in the t - f domain. More precisely, coefficients with larger magnitudes indicate the dominant signal activity in a specific frequency range. In order to decompose the signal into these sub-bands, we will use the set of rational components related to the n th segment $\mathcal{S}^n = \{c_k^n \Phi_k^n : 0 \leq k \leq N - 1\}$. Then, we arrange the coefficients in an ascending or descending order of magnitude. This is followed by partitioning \mathcal{S}^n into L number of distinct subsets which contain the components of the corresponding sub-bands. Now, the i th sub-band of the n th segment for $i = 0 \dots L - 1$ can be defined as

$$f[n-m]_i = \frac{1}{g[m]} \sum_{k=i\ell}^{(i+1)\ell-1} c_{\sigma(k)}^n \Phi_{\sigma(k)}^n, \quad (3)$$

where $\ell = N/L$ and $\sigma(k)$ denotes the permutation of the indexes corresponding to the rearrangement of the coefficients. Note that the reconstructed signal in (2) is obtained using the sum over the sub-bands:

$$f[n-m] \approx \sum_{i=0}^{L-1} f[n-m]_i. \quad (4)$$

3.2. Basis Pursuit

In order to induce the sparsity constraint to the DSTFT decomposition in (3), we employ the well-known BP algorithm [8]. BP convex optimization problem is as follows:

$$\min_x \|x\|_1 \quad \text{subject to} \quad Ax = b, \quad (5)$$

where b is an univariate signal, A is an over-complete dictionary and x is the coefficient vector of the transform. Additionally, the Basis Pursuit Denoising (BPD) as a variant of the original BP problem can be obtained as:

$$\min_x \frac{1}{2} \|b - Ax\|_2^2 + \lambda \cdot \|x\|_1. \quad (6)$$

where $\lambda > 0$ is the so-called regularization parameter.

In case of RDSTFT, A is the matrix whose columns are the synthesis functions Φ_k of the transform, x contains the coefficients c_k^n corresponding to the n th segment of the EEG signal which is equal to b . The optimization problem in (6) can be solved by using the iterative shrinkage/thresholding (IST) algorithm [10]. Here, we applied the split augmented Lagrangian shrinkage algorithm (SALSA), which was proven to converge faster than IST or other alternative algorithms [11].

4. SLEEP STAGE CLASSIFICATION IN SINGLE CHANNEL EEG

4.1. The Experimental Data

The public sleep-EDF database is used as the experimental data for sleep stage detection task. The database is a part of the PhysioNet data bank [12]. Sleep records were obtained from two different groups of subjects. First group contains 79 healthy Caucasians subjects aged 25-101, without any sleep-related medication. The second group of subjects had sleep difficulty and were under influence of temazepam medication during the recording. In this study we only consider the first group of subjects. Each sleep record was obtained using different modalities including: one horizontal Electrooculography (EOG), two EEG channels (Fpz-Cz and Pz-Oz), submental Electromyogram (EMG) envelope, oronasal airflow, and rectal body temperature. EEG and EOG signals were sampled at 100 Hz. Additionally, we used single channel (Fpz-Cz) of the EEG record in this study to detect sleep stages.

4.2. Feature Extraction

Following the basic algorithm in [5], we segment the EEG signal into epochs with 1s duration. Furthermore, we compute the optimal RDSTFT with $N = 64$ MT coefficients via HPSO. The sparse decomposition defined in Section 3 is applied in the next step. Namely, the coefficients are arranged in an ascending or descending order of magnitude followed by the partition of $L = 8$ distinct subsets. Then, each sub-band is reconstructed using the pole and one of the coefficients' subsets. Finally, the sparse representation of the frequency sub-bands is achieved by solving the optimization problem introduced in Eq. (6). Fig. 1 shows the result of the proposed decomposition technique on an EEG signal. As it can be seen, the reconstructed signal after inducing the sparsity to the frequency-bands, possesses the underlying shape of the original signal. The total energy of each frequency sub-band is extracted as the feature for discrimination between different sleep stages. Since the shortest sleep stage event in the dataset lasts for 30s, the extracted features are averaged in a sliding window with 30s duration in order to represent features of 30s epochs. In fact, RDSTFT results in a finer time-frequency resolution for shorter epochs and due to this the feature extraction method was first applied on epochs with 1s duration.

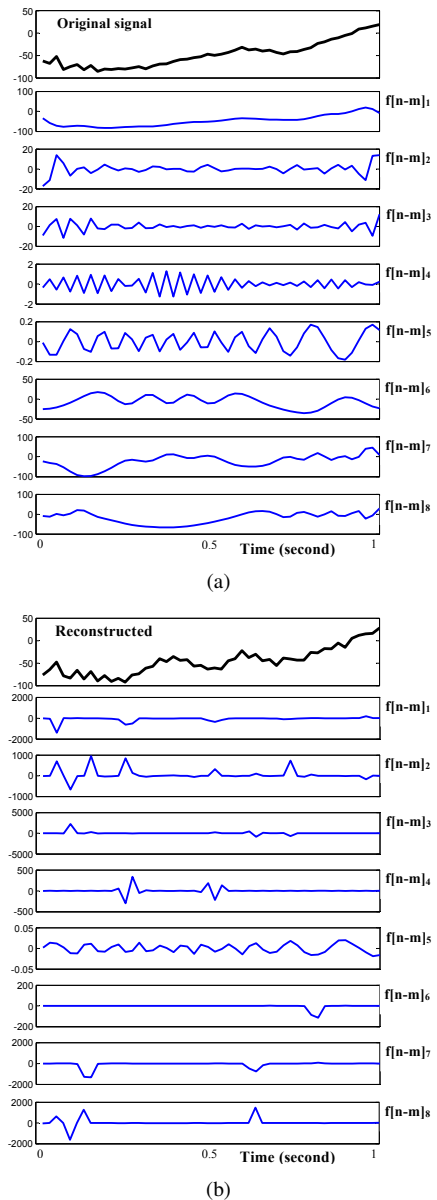


Fig. 1. Results of the proposed decomposition technique applied on one epoch of an EEG signal, a) original signal and its frequency sub-bands, b) reconstructed signal and sparse representation of the frequency sub-bands.

4.3. Classification

In this section, we use the features extracted from sparse representation of rational frequency sub-bands for supervised sleep-stage classification of EEGs. Three different classifiers which have been widely used in the literature are employed for this purpose. These classifiers are namely: 1) Multilayer Perceptron (MLP): the MLP architecture consists of 3 layers with 8 neurons in the input layer, 4 neurons in the hidden layer and 4 neurons in the output layer; 2) Support Vector

| Classifier | Sleep Stage | | | | Overall | |
|------------|--------------|---------------|--------------|--------------|--------------|--------------|
| | Wake | Stage 1 + REM | Stage 2 | Stage 3&4 | Accuracy% | F1% |
| | recall % | recall % | recall % | recall % | | |
| Lin-SVM | 97.71 | 50.33 | 79.73 | 39.30 | 88.26 | 86.43 |
| MLP | 97.53 | 69.75 | 82.55 | 75.89 | 91.63 | 91.46 |
| RF | 98.26 | 73.51 | 82.69 | 77.17 | 92.50 | 92.39 |

Table 1. Overall classification results obtained for all 39 patients using different classifiers

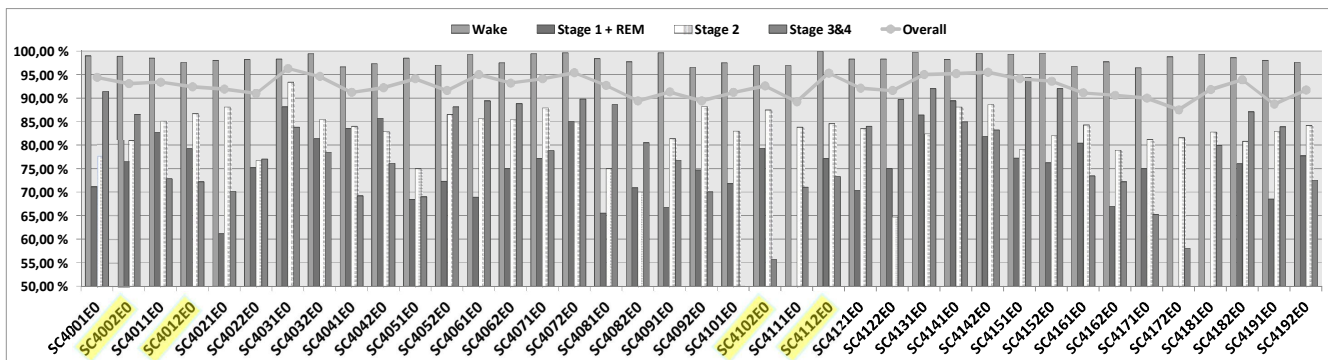


Fig. 2. Detailed classification results obtained for each subject in the dataset using RF classifier (highlighted IDs indicate subjects used in [13]).

Machines (SVMs) with linear kernel; 3) Random forest (RF): RF is an ensemble decision tree classifier, which does not require pruning compared to single conventional decision trees. In this paper, 4 different states of sleep stage discrimination are used for classification of sleep records. The 4 sleep states are namely: 1) wake, 2) stage 1 + REM, 3) stage 2, 4) slow wave sleep (SWS) consisting of stages 3 & 4. All the classifiers are individually trained for each subject using 25% of its sleep record, which is randomly picked, and tested on the rest of the sleep-record.

In all experiments, the performance of the proposed method is evaluated using 3 measures: 1) Recall or true-positive-rate which indicates the number of truly detected epochs per class and per patient; 2) overall accuracy of the classifier for all patients; 3) F1 score which is the harmonic mean of both precision and recall. The sleep records are highly imbalanced due to the presence of large number of wake epochs. Hence, it is essential to simultaneously obtain high accuracy and F1 score.

The overall results obtained using each classifier are listed in Table 1. As it can be seen, RF classifier can outperform the other two classifiers. However, the difference between the performance of the MLP and RF classifiers is not significant. The detailed results of each subject using RF classifier can be seen in Fig. 2. The lowest recall rates for SWS and stage 1+REM states are obtained for subjects SC4101E0 and SC4111E0, respectively. This is due to the limited number of epochs belonging to those states which makes the classifier

incapable of learning those patterns. The comparison of the proposed method with the results of other state-of-art methods reported in the literature for the same dataset and the same classification problem can be seen in Table 2. We note that the other methods have been only evaluated using a limited number of subjects in the dataset. In spite of that, the proposed method outperforms the others in terms of the classification accuracy. Note that only in [13] IDs of the subjects have been reported and thus the performance of the proposed method for those subjects is also included in Table 2.

| Author(s) | # of subjects | Accuracy (%) |
|-----------------------------|---------------|--------------|
| Zhu et al. (2012) [13]* | 4 | 83.19 |
| Proposed method* | 4 | 93.35 |
| Phan et al. (2013) [14] | 4 | 86.30 |
| Liu et al. (2010) [4] | 7 | 89.3 |
| Ebrahimi et al. (2008) [15] | 7 | 93.00 |
| Li et al. (2009) [16] | 8 | 81.73 |
| Proposed method | 39 | 92.50 |

Table 2. The comparison of the proposed algorithm with other state-of-the-art methods for the 4-class sleep scoring performed on the Sleep-EDF dataset

5. CONCLUSIONS AND FUTURE WORK

In this paper, the sparse decomposition of EGG signals was proposed using rational DSTFT and BP algorithm. We showed that, common low-level feature extraction methods

can then be applied on the sparse representation of the frequency sub-bands. High classification results are obtained using the proposed decomposition method and the total energy of each sub-band as the only single statistical feature. As it was justified by the experiments, the proposed method can achieve high accuracy rate and F1 score in supervised sleep staging problem. Moreover, we demonstrated that the proposed feature extraction method can represent the EEG signal in such a way that higher discrimination performance is obtained among sleep states. Thus, a better classification performance than the competing methods is achieved. While the proposed sparse representation can improve feature extraction and classification results, it can further be used for the analysis of other signals in this domain such as EEG inverse imaging and mapping, feature selection and component analysis. As our future study, we are aiming at the classification of multi-channel and multi-modal physiological data by using the proposed method. In addition, we will investigate decomposition of the signal using multiple poles and sub-sets of coefficients with overlaps.

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