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Sleep Apnoea Detection in Children using PPG envelope-based Dynamic Features

L.M. Sepúlveda-Cano, E. Gil, P. Laguna and G. Castellanos-Dominguez

Abstract— **Photopletysmography signal has been developed for monitoring of Obstructive Sleep Apnoea, in particular, whenever an apneic episode occurs, that is reflected by decreases in the photopletysmography signal amplitude fluctuation. However, other physiological events such as artifacts and deep inspiratory gasp produce sympathetic activation, being unrelated to apnea. Thus, its high sensitivity can produce misdetections and overestimate apneic episodes. In this regard, a methodology for selecting a set of relevant non–stationary features to increase the specificity of the obstructive sleep apnea detector is discussed. A time–evolving version of the standard linear multivariate decomposition is discussed to perform stochastic dimensionality reduction. As a result, performed outcomes of accuracy bring enough evidence that if using a subset of cepstral–based dynamic features, then patient classification accuracy is 83.3%. Therefore, photoplethysmography–based detection provides an adequate scheme for obstructive sleep apnea diagnosis.**

I. INTRODUCTION

Regarding the diagnosis of Obstructive Sleep Apnoea (OSA) syndrome, characterized by recurrent airflow obstruction caused by total or partial collapse of the upper airway, several strategies have been developed to decrease the number of the sleep recordings needed for usually performed polysomnography [1] that is related as an expensive and time–consuming procedure. One promising alternative is the photopletysmography (PPG) signal that is a simple, but useful method for measuring the pulsatile component of the heartbeat. Furthermore, automatic detection of time–variant decreases in the amplitude fluctuations of PPG have shown their utility for OSA diagnosis [2], [3]; nonetheless, since there is a large number of situation when PPG enveloped is affected independently of the apnoea status, then, a low ratio sensitivity/specificity is accomplished. Therefore, to better discriminate between apnoea from other PPG envelop alterations an improved set of representing features should be taken into account, particularly, stochastic modeling of dynamic features for OSA detection is to be further considered in this work.

The time—frequency (TF) representation has been proposed before for the analysis of non–stationary biomedical data. Nonetheless, without accurate models to describe properly the dynamic behavior of PPG envelope biosignals, the use of TF processing methods, may fail to provide satisfactory results. In this sense, it has been established the discriminating capability of frequency bands of biological activity between normal and pathological patterns, and for that reason, the set of TF representation—based stochastic features to be considered should be suitable estimated by time–evolving spectral subband methods.

Extraction of relevant stochastic information from dynamic feature sets has been discussed in the past, as a means to improve performance during and after training in learning processes. Thus, to get an effective feature selection algorithm, a multivariate transformation through the time axis is proposed, which is assumed to maximice the measure of relevance present in the non–stationary features by their projection onto a new space. For a dimension reduction, statistical latent variable techniques can be applied, but standard latent variable techniques clearly do not take into consideration the time–evolving nature of random biological variables, since they are grounded on a common representation that minimizes the global reconstruction error.

The aim of this study is to select a set of relevant non–stationary features, extracted from TF representation of time–dependant PPG envelope signals, to increase the specificity in the apnoea detector. This work analyzes the set comprising filter banked dynamic features that includes spectral centroids as well as the cepstral coefficients. Specifically, a time–evolving version of the standard linear multivariate decomposition is discussed throughout this paper to perform stochastic dimensionality reduction of the dynamic features in hand. The rest of the paper is organized as follows: Section II introduces materials and methods focused on generation of non–stationary features, extracted from TF representation of time–dependant PPG envelope signals. Also, the proposed methodology of stochastic training is evaluated using real PPG recordings. The attained results are discussed in Section IV. Finally, Section V presents the conclusions and discusses some possibilities for future work.

II. MATERIALS AND METHODS

A. Generation of Enhanced Dynamic Features

The PPG envelope, $y(t)$, is estimated based on the root mean square series of input PPG signal, $y_{\text{PPG}}(t)$. So, the discrete version of PPG envelope, after mean removal by a moving average filter, can be written as follows [2]:

L.M. Sepúlveda-Cano and G. Castellanos-Domínguez are with Signal Processing and Recognition Group, Universidad Nacional de Colombia, sede Manizales. lmsepulvedac,cgcastellanosd@unal.edu.co

E. Gil and P. Laguna are with Communications Technology Group (GTC), Aragón Institute of Engineering Research (I3A), ISS, University of Zaragoza, CIBER-BBN,María de Luna 1, 50018 Zaragoza, Spain edugilh,laguna@unizar.es,

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$$y(n) = \sqrt{\frac{1}{N}\sum_{k=n-(N-1)}^{n}\left(y_{\text{PPG}}(k) - \frac{1}{M}\sum_{l=k-(M-1)}^{k} y_{\text{PPG}}(l)\right)^2} \quad (1)$$

where the values for the window length of the filtering, M, and the root mean square series, N, are fixed to be 25 and twice the mean cardiac cycle, respectively.

Generally, a direct way of describing the PPG envelope, $y(t)$, in both time and frequency domains becomes its time–evolving spectral representation. Thus, for estimating TF representation of random signals, power spectral density $\boldsymbol{S}_y(t,f) \in \mathbb{R}^+$ is commonly used, which for a given biosignal, $y(t)$, is directly represented by the *spectrogram*

$$\boldsymbol{S}_y(t,f) = \left|\int_T y(\tau)\phi(\tau - t)e^{-j2\pi f\tau}d\tau\right|^2, \quad t,\tau \in T,$$

Supported on classical Fourier Transform, the Short Time version (termed STFT) introduces a time localization concept by using a tapering window function of short duration, ϕ, that is going along the studied biosignal, $y(t)$.

B. Dynamic features

A *dynamic feature* refers to numeric values that represent measures changing over some associated dimension, with the purpose of combine the frequency and magnitude information from the power spectrum:

- *Linear Frequency Cepstral Coefficients* (LFCC), extracted by Discrete Cosine Transform of triangular log–filter banks, $\{F_m[k] : m = 1,\ldots,n_M\}$, linearly spaced in the frequency domain:

$$x_n(l) = \sum_{m=1}^{n_M} \log\left(s_m\left(l\right)\right)\cos\left(n\left(m - \frac{1}{2}\frac{\pi}{p}\right)\right) \quad (2)$$

  where p is the number of desired LFCC features to be considered, and $s_m(l)$ is the weighted sum of each frequency filter response set, $s_m(l) = \sum_{k=1}^{n_K} S_y(l,k)F_m(k)$, being m, l and k the indexes for filter ordinal, time, and frequency axes, respectively; n_K stands for the number of samples in the frequency domain.
- *Spectral Centroids*, that are computed for each filter in the frequency domain, $F'_m(k)$, by:

$$x_n(l) = \frac{\sum_{k=1}^{n_K} kF'_n\left(k\right)S_y^{\gamma}\left(l,k\right)}{\sum_{k=1}^{n_K} F'_n\left(k\right)S_y^{\gamma}\left(l,k\right)} \quad (3)$$

  where γ is a parameter representing the dynamic range of the spectrum that is used for computation of the centroid. The filters $F'_n(k)$ are linearly distributed along the spectrum
- *Energy of Centroids*, is the energy around each centroid. It can be also considered for a fixed bandwidth Δk and is computed by means of:

$$x_n(l) = \sum_{k=\hat{x}_n(l)-\Delta k}^{\hat{x}_n(l)+\Delta k} S_y\left(l,k\right) \quad (4)$$

  where $\hat{x}_n(l)$ is the actual value of the time–variant centroid that is estimated by (3).

C. Relevance Analysis of Stochastic Features

Because of high computational cost of stochastic feature–based training, dimension reduction of input spaces is to be carried out, being latent variable techniques widely used for this aim that finds a transformation reducing p–dimensional stochastic feature arrangement, $\boldsymbol{\Xi} \in \mathbb{R}^{p\times T}$, into q–dimensional stochastic set, $\boldsymbol{Z} \in \mathbb{R}^{q\times T}$, $q \leq p$, in such a way that the data information is maximally preserved. Besides, as the relevance function, $g \in \mathbb{R}$, the evaluation measure of transformation is given that distinguishes variables effectively representing the subjacent physiological phenomena, termed *relevant stochastic features*.

The set of stochastic features, $\{\boldsymbol{x}_i\}$, is represented by the observation assemble comprising N objects that are disposed in the input observation matrix $\boldsymbol{X}_{\boldsymbol{\Xi}} = [X_1|\cdots|X_i|\cdots|X_N]$. In turn, every object, denoted as X_i, $i = 1,\ldots,N$, is described by the respective observation set of time–variant arrangements, $\{\boldsymbol{x}_{ji} \subset \boldsymbol{\Xi}, j = 1,\ldots,p\}$, such that, $X_i = [\boldsymbol{x}_{1i}|\cdots|\boldsymbol{x}_{ji}|\cdots|\boldsymbol{x}_{pi}]^\top$, $X_i \in \mathbb{R}^{p\times T}$, where $\boldsymbol{x}_{ji} = [x_{ji}(1)\ldots x_{ji}(t)\ \ldots\ x_{ji}(T)]$ is each one of the measured or estimated short–term features from biosignal recordings, equally sampled evolving through the time, and being $x_{ij}(t)$, the j–th stochastic feature for the i–th object upon a concrete t instant of time.

Given $\boldsymbol{X}_{\boldsymbol{\Xi}}$, there will be a couple of orthonormal matrixes, $\boldsymbol{U} \in \mathbb{R}^{N\times N}, \boldsymbol{V} \in \mathbb{R}^{pT\times pT}$, plus diagonal matrix $\boldsymbol{\Sigma}_{\boldsymbol{X}}$, as well, so that a simple linear decomposition takes place, i.e., $\boldsymbol{X}_{\boldsymbol{\Xi}} = \boldsymbol{U}\boldsymbol{\Sigma}_{\boldsymbol{X}}\boldsymbol{V}^\top$, where $\boldsymbol{\Sigma}_{\boldsymbol{X}} \in \mathbb{R}^{pT\times pT}$ holds first ordered q as most relevant eigenvalues ν of $\boldsymbol{X}_{\boldsymbol{\Xi}}$, that implies the relevance measure to be considered.The minimum mean squared–based error is assumed as the evaluation measure of transformation, $g(\boldsymbol{X}_{\boldsymbol{\Xi}}, \boldsymbol{Z}) \sim \min \boldsymbol{E}\{\|\boldsymbol{\Xi} - \boldsymbol{Z}\|_2\}$ (where $\boldsymbol{E}\{\cdot\}$ stands for expectation operator), that is, maximum variance is preferred as relevance measure, when the following estimation of covariance matrix is carried out:

$$\text{cov}\{\boldsymbol{X}_{\boldsymbol{\Xi}}\} = \boldsymbol{X}_{\boldsymbol{\Xi}}^\top\boldsymbol{X}_{\boldsymbol{\Xi}} = \boldsymbol{V}\boldsymbol{\Sigma}_{\boldsymbol{X}}^2\boldsymbol{V}^\top \quad (5)$$

To make clear the contribution of each time–variant value $x_{ij}(t)$, expression (5) can be further extended in the form:

$$\boldsymbol{X}_{\boldsymbol{\Xi}}^\top\boldsymbol{X}_{\boldsymbol{\Xi}} = \sum_{j=1}^{p}\nu_j^2 V_j V_j^\top, \quad (6)$$

where V_j is the j–th column of matrix $\boldsymbol{V}$.

Consequently, the amount of relevance captured at every moment t by the singular value decomposition, that is associated to the whole set of features is assessed as the following time–variant relevance measure:

$$g(\boldsymbol{X}_{\boldsymbol{\Xi}}, \boldsymbol{Z}; t) = \sum_{j=1}^{q}|\nu_j^2 V_j|, \quad (7)$$

Therefore, dimension reduction is carried out by adapting in time commonly used latent variable techniques (by example, the one expressed by Eq. (5)), in such a way, that the data information is maximally preserved, given a relevance function as evaluation measure of time–variant transformation, and therefore, distinguishing relevant stochastic features.

III. EXPERIMENTAL SETUP

Based on relevance analysis of dynamic features that are extracted from TF representation of PPG envelope, the proposed methodology for diagnosing obstructive sleep apnoea appraises next stages: a) Preprocessing, b) Enhancement of TF representation, c) Dynamic feature extraction embracing dimension reduction of TF representation–derived time series, and d) OSA detection.

A. Clinic Photoplethysmography Database and Preprocessing

This study uses 21 polysomnography recordings of children, as detailedly described in [3]. The children aging within 4.5 ± 2 years were referred to the Miguel Servet Children's Hospital in Zaragoza for suspected sleep–disordered breathing. PPG and arterial oxygen saturation (SaO_2) were measured continuously using a pulse oximeter. Recordings were stored with a sample rate of 100 Hz. OSA evaluation from PSG data were scored by clinical experts using the standard procedures. Ten children were diagnosed with OSA whereas the remained eleven were diagnosed as normal.

B. TF Representation Enhancement and Feature Generation

Based on spectral PPG envelope properties, the STFT–based quadratic spectrogram is computed by sliding Hamming windows for the following set of estimation TF representation parameters: 37.5 ms processing window length, 50 % of overlapping, and 512 frequency bins. In respect to calculation of cepstral coefficients and centroids, the following working parameters are to be determined [4]: the initial number of time–variant features, the number of bank filters, the impulse response and its overlap over frequency domain. The input data space includes the following 39 TF representation–based dynamic features to be further studied: the first 22 spectral centroids and their respective energy (estimated by using Hamming filters with 30% overlap, linear response distribution, and fixing $\gamma = 1$), and the first 17 time series of vector cepstral coefficients that are computed by 48 triangular response filters with 50% overlap.

C. Estimation of Relevance Weights of Dynamic Features

For the concrete case of OSA diagnosing, selection of the best set of features can be achieved using, al least, two different combining approaches of comparison [5]: Firstly, when taking a partially divided set having the same principle of generation. Secondly, when the best contours are chosen among the whole set of features no matter on their physical meaning. In this work, both combining approaches of dynamic features are studied in terms of dimension reduction, but also of accuracy performance. The normalized relevance weights, which are estimated according to discussed methodology of relevance analysis for stochastic processes, are depicted in Figure 1, being ordered by ordinal feature number, which are calculated when taking the whole set of dynamic features.

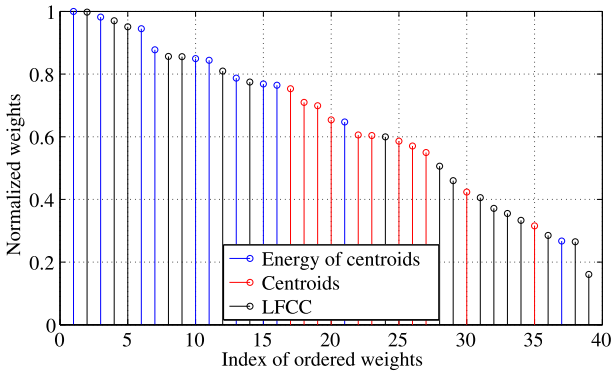

Fig. 1. On computing relevance weights for considered combining approaches of comparison among dynamic features.

D. Performed Classification Accuracy

Throughout the following training procedures, the metric to adjust the different schemes of considered parameterizations is the classification accuracy for the automatic OSA detection, which is estimated using a simple $k-nn$ classifier.

Each patient is diagnosed based on those decisions made from the set of fragments measured for him. So a rule to determine when a patient with a given number of pathological fragments is considered as a pathologic subject is needed. To do this, the percentage of time under pathologic fragments was considered and this threshold was selected for maximizing Se and Sp, ratio at the ROC curve.

TABLE I
CLASSIFICATION OF PATIENT FOR TRAINING BASED ON PARTIALLY DIVIDED SET OF DYNAMIC FEATURES

Dynamic feature set	Se [%]	S_p [%]	Acc [%]
Energy of Centroids	70.00	87.50	73.68
Centroids	80.00	87.50	83.33
LFCC	90.00	75.00	83.33
Full set	80.00	87.50	83.33

Table I summarizes the performed patient classification accuracy for both considered combining approaches of dynamic features (partial and full set). In accordance with the discussed approach of relevance analysis, the LFCC and Centroids subsets of dynamic features reach the better accuracy that is similar to the one achieved for the whole training set. As a result, both sets should be strongly considered for OSA diagnosing with the advantage that the each performed time–evolving parameter is related to a fixed spectral subband, and thus, leading to easer clinical interpretation.

IV. DISCUSSION

It should be remarked that the main goal of present paper is to use a complex of signal processing algorithms for

the improvement in OSA diagnosis from PPG recordings, as an alternative for sleep apnea screening with the added benefit of low cost and simplicity. The methodology lies on the hypothesis that each time–dependent characteristic holds a relative associated weight of relevance, and in this connection, the results also evidence the following aspects to take into consideration:

– Feature enhancement is performed by means of non-parametric spectrogram–based TF representation that had been reported to be appropriate for the analysis of nonstationary biological signals consisting of different frequency components. Nonetheless, for the discussed methodology for OSA detection, needed TF representation enhancement for dynamic feature extraction can be performed by using more elaborated approaches: wavelet–based scalograms, projection pursuit, by using time frequency distributions, etc., as discussed in [4]. Yet, no matter which particular TF representation estimation method is used, the final result is a large data matrix containing the time-frequency pattern, which has to be transformed into a feature vector for classification purposes holding the most relevant information in a compact fashion.
– With regard to feature extraction and selection, proposed methodology for relevance analysis of dynamic relevance is based on time–adapted linear component approach. As a measure of relevance, the maximum variance is assumed. Specifically, time–adapted PCA version is discussed throughout this paper as unsupervised method to perform relevance analysis of considered set of stochastic features. Though proposed methodology of relevance analysis can extended to other techniques linear component decomposition, as shown in [6].

V. CONCLUSIONS

A new methodology for OSA detection is explored, which is based on relevance analysis of dynamic features extracted from nonparametric TF representation of the recordings of PPG envelope. Particularly, a time–evolving version of the standard PCA is discussed that performs stochastic dimensionality reduction of the dynamic features in hand. Discussed methodology of relevance analysis benefits of the dynamic properties of the time–evolving spectral parameters, during either transient physiological or pathological episodes. As a result, PPG can be considered as a promising alternative to reduce de the number of the PSG sleep recordings.

In addition, two different combining approaches for selecting the best set of contours are studied: Firstly, when taking dynamic features having the same principle of generation. Secondly, when the best features are chosen despite of their physical meaning. In this case, the latter approach turns to more suitable because of the convenient physical interpretation of selected set of features and provided accuracy of selection is more commonly used because of the convenient physical interpretation of selected set of features. Furthermore, it has been established that the LFCC and Centroids subsets of dynamic features should be strongly considered for OSA diagnosing since it increases the specificity in the apnoea detector. Both subsets display a patient classification accuracy of 83.33%, while in [7] is reported an accuracy of 80%; consequently, the advantage of the method proposed in this paper to increase the specificity of the obstructive sleep apnea detector is evident.

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