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On Determining Available Stochastic Features by Spectral Splitting in Obstructive Sleep Apnea Detection

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***Abstract*— Heart rate variability (HRV) is one of the promising directions for a simple and noninvasive way for obstructive sleep apnea syndrome detection. The time–frequency representations has been proposed before to investigate the non-stationary properties of the HRV during either transient physiological or pathological episodes. Within the framework of the filter–banked feature extraction, estimation of the spectral splitting for stochastic features extraction is an open issue. Usually, this splitting is fixed empirically without taking into account the actual informative distribution of time–frequency representations. In the present work, a relevance–based approach that aims to find a priori a boundaries in the frequency domain for the spectral splitting upon *t–f* planes is proposed. Results show that the approach is able to find the most informative frequency bands, achieving accuracy rate over 75%.**

I. INTRODUCTION

The obstructive sleep apnea syndrome (OSA) is a common sleep disorder, characterized by obstruction in the airflow. To perform OSA diagnosis, detection of repetitive episodes of apnea and hypopnea during sleep is carried out, mostly, by attended overnight polysomnography in a sleep laboratory. However, regarding to standard polysomnography test the main disadvantage is the high amount of information required to be analyzed [1], [2]. One of the promising directions for a simple method for OSA detection is provided by an analysis based on the heart rate variability (HRV) [3]. In this line of analysis, the time–frequency (*t–f*) representations, has been proposed before to investigate the time–variant properties of the spectral parameters during either transient physiological or pathological episodes [4]. Typically, two frequency bands are considered for OSA detection: frequencies between 0.04 and 0.15 Hz (termed low band LF), and frequencies between 0.15 and 0.5 Hz (termed high band HF) [5]; nevertheless, there are some normal *t–f* maps whose waveform resembles like pathological ones, and vice versa; so, the spatial distribution of the energy in each sub–band is not clear; for this reason, a set of *t–f*–based stochastic features is considered. Usually, the tuning of the suitable spectral splitting for the stochastic feature extraction is carried out by dint of find the frequency subbands according to the high accuracy [5]. The main problem of this approach (called *heuristic*), is the uncertainty about the physical meaning of the extracted features and the fact that all the process is centered over an unknown number of iterations. Therefore, it is necessary to find an approach for frequency sub–band selection in order to achieve the spectral splitting for stochastic feature extraction. This study proposes a relevance–based approach that aims to find a priori a boundaries in the frequency domain for the spectral splitting. The main idea is to improve the use of the more relevant frequency bands for OSA detection, with end to extract filter–bank based features from the HRV signal. Three different relevance measures are considered: maximum variance as non-supervised technique, and symmetrical uncertainty and linear correlation as supervised techniques. For the sake of comparison, the typical split approach based on performance measures is tested. It must be noted that because of easier medical interpretation, each way of spectral splitting over *t–f* maps is carried out separately for each one of the two bands of interest (LF and HF).

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II. MATERIALS AND METHODS

A. Generation of t-f based Stochastic Features

Generally, a direct way of describing the HRV time series, $y(t)$, in both time and frequency (*t–f*) domains becomes its time–evolving spectral representation. In particular, power spectral density is commonly used that is directly represented by the *spectrogram*:

$$\boldsymbol{S}_y(t,f) = \left| \int_T y(\tau)\phi(\tau - t)e^{-j2\pi f\tau}d\tau \right|^2 \qquad (1)$$

where $t, \tau \in T, f \in \Delta F,\ \boldsymbol{S}_y(t,f) \in \mathbb{R}^+$.

Supported on classical Fourier Transform, the Short Time version (STFT) introduces a time localization concept by using a tapering window function of short duration, ϕ, that is going along the underlaying biosignal, $y(t)$. Estimated *t–f* representation matrix, $\boldsymbol{S}_y \in \mathbb{R}^{T\times\Delta F}$, can be represented by the row vectors, $\boldsymbol{S}_y = [\boldsymbol{s}_1 \ldots \boldsymbol{s}_f \ldots \boldsymbol{s}_{\Delta F}]^\top$, where $\boldsymbol{s}_f = [s(f,1)\ldots s(f,t)\ldots(f,T)]$ is each one of the estimated spectral decomposition at frequency f, and equally sampled through the time axis t. In this study, OSA detection is conducted by the set of short–time filter–banked features $\{\boldsymbol{x}_n : n = 1,\ldots,p\}$. This multi–band scheme splits the whole frequency range ΔF into several sub–bands $\{F_n\}$, comprising a set of adjacent spectral components $\{\boldsymbol{s}_f\}$, from where stochastic features are extracted independently. That is, each assessed frequency sub–band F_n from end to end along the time domain holds the boundary of a single stochastic feature $\boldsymbol{x}_n$. In turn, each vector feature is attained by filter bank modeling. For the sake of simplicity, this study uses the set of *Linear Frequency Cepstral Coefficients* (LFCC) as proposed in [5].

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B. Spectral Splitting upon t–f Planes

Within the framework of the filter–banked feature extraction, estimation of both the number of stochastic features p as well as the the number of filter banks n_F is provided by using spectral splitting upon *t–f* plane. To this end, each assessed frequency division from end to end along the time domain holds the boundary of a single filter-banked stochastic feature. The set of spectral partitions is determined by one of the following approaches:

Heuristic Splitting: The selected bandwidth of interest is split in equally spaced sub–band partitions obtaining information about the spatial distribution of the energy. The main idea is to cover all the possible combinations between the number of filter banks n_F and the number of features i.e., an iterative process takes place by which the number of filters is stepwise incremented. To evaluate the filter-banked feature, a wrapper measure of performance is accomplished after each iteration. The number of LFCC features providing the maximum value of accuracy is selected as the proper number p of stochastic features to be considered.

Relevance–based Splitting: In this case, the frequency band boundaries are determined by introducing a filter–type measure of relevance to evaluate the whole *t–f* plane. Since each feature vector $\boldsymbol{x}_n$ contains a different amount of useful information for OSA detection, the proposed relevance–based splitting scheme emphasizes the most relevant sub–bands. That is, the higher relevant the set of spectral components $\{\boldsymbol{s}_f\}$ of sub–band F_n, the more important the derived stochastic feature $\boldsymbol{x}_n$. The following supervised measures of relevance as evaluation criteria are assessed [6]:

a. *Linear Label-conditioned correlation* that is given by

$$\rho(s(t,f)|\boldsymbol{c}) = \left| \frac{\boldsymbol{E}\{(s^{(i)}(t,f) - \overline{s(t,f)})(c^{(i)} - \overline{c})\}}{\sqrt{\boldsymbol{E}\{(s^{(i)}(t,f) - \overline{s(t,f)})\}\boldsymbol{E}\{(c^{(k)} - \overline{c})\}}} \right|, \quad (2)$$

where $\overline{s^{(i)}(t,f)} = \boldsymbol{E}\{s^{(i)}(t,f) : \forall i\}$, the measured value of $s(t,f))$ for the $i-$ object, $i = 1,\ldots,M$, and $\overline{c^{(i)}} = \boldsymbol{E}\{c^{(i)} : \forall i\}$. Likewise, $c^{(i)}$ is the label of $i-$ object given to the $s^{(i)}(t,f)$. The notation $\boldsymbol{E}\{\cdot : \forall\lambda\}$ stands for the expectation operator over variable λ.

b. *Symmetrical Label-conditioned Uncertainty* given by:

$$\upsilon(s(t,f)|\boldsymbol{c}) = \frac{\boldsymbol{H}\{s^{(i)}(t,f) : \forall i\} - \boldsymbol{H}\{s^{(i)}(t,f)|c^{(i)}\}}{\boldsymbol{H}\{s^{(i)}(t,f) : \forall i\} - \boldsymbol{H}\{c^{(i)} : \forall i\}} \quad (3)$$

being $\boldsymbol{H}\{\cdot : \forall\lambda\}$ the entropy operator over variable λ.

c. *Stochastic Variability:* The following unsupervised measure of time–variant relevance is assessed [5]:

$$\boldsymbol{g}(\boldsymbol{S}_y;\tau) = [\chi(1)\ \cdots\ \chi(\tau)\ \cdots\ \chi(pT)]^\top, \quad (4)$$

where $\chi(\tau) = \boldsymbol{E}\{|\lambda_j^2 v_j(\tau)|\}$, $\{\lambda_j : j = 1,\ldots,q\}$ is the set of most relevant eigenvalues of matrix $\boldsymbol{S}_y$, and scalar $v_j(\tau)$ is the respective element at τ moment, and $\tau = 1,\ldots,pT$ indexes each one of the relevance values computed for the whole time–variant data set. To determine distinctly the relevance related to each one of the stochastic variables, Eq. (4) can be reallocated to the relevance matrix, $[\boldsymbol{g}_1(\boldsymbol{S}_y;t)\cdots\boldsymbol{g}_f(\boldsymbol{S}_y;t)\cdots\boldsymbol{g}_{\triangle F}(\boldsymbol{S}_y;t)]^\top$, where each row $\boldsymbol{g}_f(\boldsymbol{S}_y;t) = [\chi((f-1)T+1)\ldots\chi(t)\ldots\chi(fT)] \in \mathbb{R}^{T\times 1}$ that is a sectioned version of vector $\boldsymbol{g}(\boldsymbol{S}_y;\tau)$ plainly holds the contribution of the $\boldsymbol{s}_f-$ stochastic feature along the fixed moments of time.

To measure the contribution of each spectral component, a simple average is accomplished, i.e.,

$$\rho(\boldsymbol{s}_f|\boldsymbol{c}) = \boldsymbol{E}\{\rho(s^{(i)}(t,f)|\boldsymbol{c}) : \forall t\} \quad (5a)$$

$$\upsilon(\boldsymbol{s}_f|\boldsymbol{c}) = \boldsymbol{E}\{\upsilon(s^{(i)}(t,f)|\boldsymbol{c}) : \forall t\} \quad (5b)$$

$$g_f(\boldsymbol{s}_f) = \boldsymbol{E}\{\boldsymbol{g}_f(\boldsymbol{S}_y;\tau) : \forall\tau\}, \quad (5c)$$

Because of high level of correlation between each pair of adjacent spectral components $\{\boldsymbol{s}_f, \boldsymbol{s}_{f+1}\}$, the main assumption is that the minimum values of their measured contribution should be considered as the boundaries of the spectral sub–bands.

III. EXPERIMENTAL SETUP

A. Database

This collection holds $M = 70$ electrocardiographic recordings from PhysioNet [7], each one including a set of reference annotations added every minute of the recording indicating either the presence or absence of apnoea during each segment of time. The recordings were subdivided in three groups: apneic patients, with more than 100 min in apnea, borderline patients, with total apnea duration more than 5 and less than 99 min and control or normal patients, with less than 5 min in apnea. From the database, 25 recordings were used as a training set for the classification algorithms. A second group with 25 recordings was used as a test set to measure the performance of the algorithms, as recommended in [7].

B. Time–Frequency Representations Enhancement of Estimated HRV Time Series

Automatic OSA diagnosis requires the extraction of HRV time series from each ECG recording, which in turn can be estimated precisely if an accurate recognition of the *QRS* complex fiducial point is achieved. In this work, complex detection is carried out by the procedure described in [5]. Then, based on spectral HRV signal properties, the STFT–based quadratic spectrogram is computed by sliding Hamming windows for the following set of estimation parameters: 32.5 ms processing window length, 50% of overlapping, and 512 frequency bins.

C. Splitting in Frequency-Domain Plane

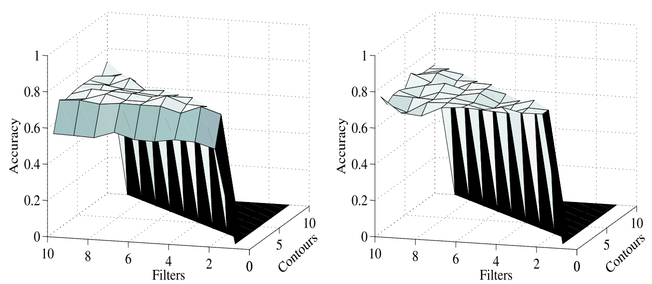
It must be noted that because of easier medical interpretation, each way of spectral splitting over *t–f* maps is carried out separately for each one of the two bands of interest (LF and HF).

*Selection of Frequency Sub–bands by Heuristic Approach:*The procedure for tuning the heuristic approach is described in the algorithm 1

Input: HRV
Output: Frequency bands
foreach *Class* k **do**
  foreach *Observation* i **do**
    1) Compute *t–f* map $(k,i) \in \mathbb{R}^{\Delta F \times T}$ of the HRV signal;
  end
end
foreach *Filter bank* $j = 1 : n_{F_{max}}$ **do**
  1) Compute j stochastic features corresponding to j triangular filters linearly spaced over the frequency domain;
  foreach *Features subset* $p = 1 : j$ **do**
    1) Create a features subset corresponding to the first p LFCC;
    2) Dimension reduction of the input data;
    3) Obtain the accuracy for this feature subset with a *k–nn* classifier
  end
end
1) Select the frequency bands (n_F and p) when the accuracy rate be maximized;

Algorithm 1: Algorithm for the frequency bands selection by heuristic approach

The number of filters n_F and the number of dynamic features p, is selected according to the maximum value of accuracy reached with a basic *k–nn* classifier. Figure 1 shows the tuning of the approach, Figure 1(a) for the low frequency band and Figure 1(b) for the high frequency band.



(a) Low band tuning (b) High band tuning

Fig. 1. On adjusting the number of *t–f*–based frequency bands.

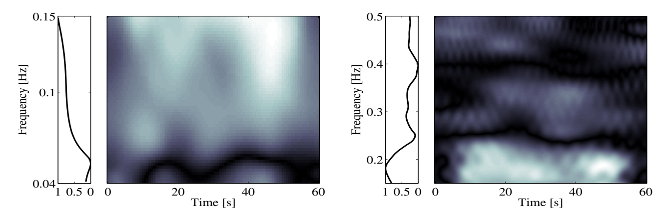
Finally, the input data space includes the following 6 TFR–based stochastic features to be further studied: the first 3 time series of cepstral coefficients vector that are computed by 5 triangular response filters, with 10% overlap for the low band; and the first 3 time series of cepstral coefficients vector that are computed by 7 triangular response filters, with 10% overlap for the high band.

Relevance–based Approach for Frequency Sub–bands Selection: For the concrete case of OSA diagnosing, the splitting of the frequency axis for stochastic features extraction, can be achieved using the relevance obtained for each spectral sub–band. Three different measures are considered: relevance based on linear correlation (Eq. 2), relevance based on symmetrical uncertainty (Eq. 3) and relevance based on maximum variance (Eq. 4). The algorithm 2 describes the process for splitting the frequency axis by means of the relevance measures.

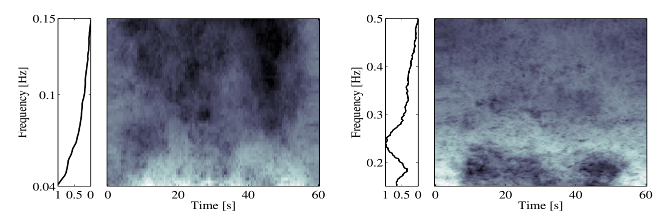
Input: HRV
Output: Frequency bands
foreach *Class* k **do**
  foreach *Observation* i **do**
    1) Calculate *t–f* map $(k,i) \in \mathbb{R}^{\Delta F \times T}$ of the HRV signal;
    2) Transform *t–f* representation into a vector $\in \mathbb{R}^{1 \times \Delta FT}$;
  end
end
1) Create a matrix concatenating the *t–f* representations vectors $\in \mathbb{R}^{N \times \Delta FT}$;
2) Calculate relevance for each column of the matrix $\in \mathbb{R}^{1 \times \Delta FT}$;
3) Reshape the relevance vector into a relevance matrix $\in \mathbb{R}^{\Delta F \times T}$;
4) Calculate a column vector containing the mean value of each row of the relevance matrix $\in \mathbb{R}^{\Delta F \times 1}$;
5) Select the frequency bands where the relevance presents significant changes on its behavior i.e. the local minimums of the curve;

Algorithm 2: Algorithm for the frequency bands selection by relevance analysis

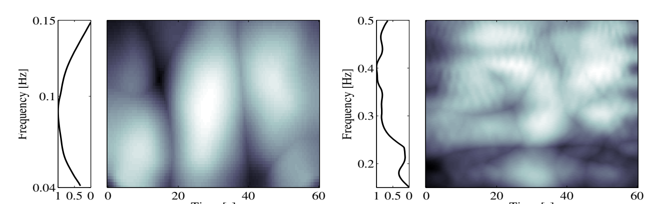
Figure 2 shows the relevance matrices obtained with the different measures along with the contribution of each spectral sub–band in the left plots, as is proposed in Eq. 5. Table I shows the selected frequency bands. Each band includes 1 time series of cepstral coefficients vector that is computed by 1 triangular response filter.



(a) Low band - linear correlation (b) High band - linear correlation



(c) Low band - symmetrical uncertainty (d) High band - symmetrical uncertainty



(e) Low band - maximum variance (f) High band - maximum variance

Fig. 2. Selection of the frequency bands using relevance analysis.

IV. RESULTS AND DISCUSSION

The stochastic features obtained for each band individually, are used to create a new set of features. Because of high computational cost of stochastic feature-based training,

TABLE I

FREQUENCY BANDS SELECTION

Relevance		Frequency Bands [Hz]	# Features
Linear Correlation	LF	$0.04-0.05, 0.05-0.11$ $0.11-0.15$	3
	HF	$0.15-0.24, 0.24-0.31$ $0.31-0.39, 0.39-0.50$	4
Sym Uncertainty	LF	$0.04-0.06, 0.06-0.08$ $0.08-0.12, 0.12-0.15$	4
	HF	$0.15-0.19, 0.19-0.30$ $0.30-0.50$	4
Maximun Variance	LF	$0.04-0.07, 0.07-0.10$ $0.10-0.15$	3
	HF	$0.15-0.23, 0.23-0.34$ $0.34-0.46, 0.46-0.50$	4

a dimension reduction of the input space is carried out by means of a time–evolving version of the standard PCA, as in [5]. The different approaches are tested and compared using a simple *k–nn* classifier, followed by a cross-validation procedure, which consists on randomly select the same number of observations for the training group and the test group. In turn, Table II summarizes the minute–by–minute classification accuracy performed for the different approaches for spectral splitting and its respective set of stochastic features.

TABLE II

CLASSIFICATION ACCURACY

Approach		# Features	Acc [%]
Heursitic		6	75.42 ± 0.88
Relevance	Linear Correlation	7	75.64 ± 1.14
	Symmetrical Uncertainty	7	74.80 ± 0.68
	Maximun Variance	7	75.22 ± 0.58

Results show that both heuristic approach, and the relevance-based approach, present similar performance, over 75%. As the spectral splitting for the first approach is centered over an unknown number of iterations on the accuracy rate, with the aim of find the most informative frequency sub–bands, it can be concluded that the relevance-based approach is able to find a priori a boundaries in the frequency domain for the extraction of the stochastic features in a less complex way. Besides, it can be noted that the three different measures, although find different behaviors in the relevance, as is shown in Table I, the results do not change significantly. Then it is difficult to select one single measure as the most appropriate. Nevertheless, the measure based on maximum–variance is computed taking into account the influence of each variable over the whole set of features, and not only the relation between the data and its respective label class; so, this relevance measure could be directly associated with the signal dynamic, which is convenient for the concrete case of spectral splitting.

V. CONCLUSIONS

Several approaches for the spectral splitting upon *t–f* planes in the concrete case of OSA detection are studied. The first one, select the frequency bands as a compromise between the number of filters n_F and the number of stochastic features p so that the classification accuracy be maximized. The second one is based on finding the frequency boundaries by means of a relevance measure, with aim to compute a stochastic feature derived from each spectral sub-band, in this case, cepstral coefficients. Results show the advantage of the relevance based approach, due to the procedure for finding the frequency bands is easier and the accuracy rates are similar than the ones obtained with the heuristic approach. Besides, the computational load is lower, since the frequency bands selection is not achieved by means of a performance measure. Regarding to feature extraction and selection, both approaches show a classification accuracy of 75%, while in [8] is reported an accuracy of 73%; consequently, the advantage of the method proposed in this is evident. Nevertheless, previous works show higher accuracy but with more complex methods or more computed features [9].

As future work is proposed, in first instance, the use of parallel combining *k*–nn classifiers, with aim to discriminate between normal and pathological signals due to the different dynamics in the filter-banked stochastic features, corresponding to each frequency sub–band. Besides, is proposed the use of different relevance measures that take into account both the relation among spectral components and the relation with the class labels.

VI. ACKNOWLEDGMENTS

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