QUANTIFICATION OF RESPIRATORY INFLUENCE IN HEART RATE VARIABILITY THROUGH WAVELET PACKETS DECOMPOSITION ALGORITHM.

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ABSTRACT
Respiratory Sinus Arrhythmia (RSA) induces cyclic variations, synchronous with respiration, in the RR interval series. Quantification of RSA is important for the correct separation between sympathetic and parasympathetic components of HRV and for the analysis of Autonomic Nervous System (ANS) activity. In this paper we propose a Wavelet packets subband decomposition algorithm for the extraction of respiratory-related component of RR variability. Wavelet Packets are used to filter the RR interval and respiratory series and to generate a set of orthonormal sub-band signals. An Autoregressive with eXogenous input (ARX) model is used to describe the relationships between the two signals in the different sub-bands. Starting from the parameters of the different sub-band models it is possible reconstruct the respiratory related component in full-band. A few preliminary results will be presented to discuss the performance of the proposed approach and to show that the new approach is able to provide a better reconstruction of the RSA than tradition full-band methods.

I. INTRODUCTION
It is well known that the spectral analysis of Heart Rate Variability (HRV) signals provide information on Autonomic Nervous System (ANS) activity [1]. The Low Frequency (LF) and the High Frequency (HF) components, which characterize the HRV spectrum, have been related to sympathetic and parasympathetic branches of the ANS. In particular, the LF component (centered around 0.1 Hz) increases in presence of an increased sympathetic activity [2], while the HF component (centered around respiratory frequency) is mainly modulated by vagal activity [2][3]. During controlled rest condition, the regular breathing produces a well-defined spectral component around the respiratory frequency. However, in real conditions, respiration can be extremely variable and irregular, affecting the HRV spectrum in a wider range of frequency such as in presence of stationary wide-band respiratory activity [5][6]. Sometimes the respiratory peak may also overlap LF component [7]. In these cases, the correct quantification of RSA is difficult and the separation between respiratory-related and -unrelated RR variability may be crucial.

In this paper, a novel method for the quantification of RSA on HRV series is presented. The method describes the respiratory influence on HRV through a Autoregressive with eXogenous input (ARX) model [8], whose parameters are estimated through least-square (LS) algorithm. Usually the estimation of model parameters is performed on the original RR and respiratory series. Here, parallel estimation is performed on the set of orthonormal sub-series which are generated through a Wavelet Packets decomposition tree [9]. Thank to the properties of the WP decomposition framework the generated sub-series carry information at different scale and different frequency. Model identification, when performed on the WP generated sub-signals, allows to more deeply exploit the characteristics of the relationships between respiration and HRV and lead to a more precise quantification of the different rhythms which characterize HRV.

II. METHOD
Wavelet-packet decomposition. The tachogram (i.e. the beat-to-beat series of the RR interval) and respirogram (i.e. the beat-to-beat respiratory series obtained by sampling the continuous respiration signal in correspondence of each R peak) were decomposed using a Daubechies-20 wavelet [10]. Each signal is decomposed by successive low-pass, high-pass filtering and subsequent sub-sampling according to the classical tree structure of Wavelet Packets [9]. In such a way, we obtain a multiresolution orthonormal description of the original signals. Each sub-signal contains information, in different frequency ranges, on the relationships...
between respiration and HRV. Among all the possible \( N_J = 1 + (N_{J-1})^2 \), i.e. the number of allowed decomposition tree at level \( J \), the scheme, which provide the best fitting between estimated and simulated RSA, was selected.

Model identification. Relationships between HRV and respiration are described by an ARX model. Respiratory influence is seen as an exogenous input to short term HRV [8]. According to this model two contributions characterize the RR short term variability (See Figure 1): a respiratory related (RSA) and a non-respiratory (NRSA) components. The first is modeled by the \( M_t \) block, while the second is described by \( M_r \). Through the identification of the model parameters it is possible to separate these two contributions. A linear least square algorithm (LS) [11] is used at this regard.

III. Simulation

In order to test the performance of the proposed algorithm, two synthetic signals, which mimic the characteristic of RR tachogram (\( t \)) and respirogram (\( r \)) beat-to-beat series, were created. \( r \) is obtained as a wide-band process, generated as the output of AR(6) model. The frequency contents of the generated signal is plotted in Figure 2 (b). \( t \) is obtained as the sum of two contributions: i) the respiratory correlated component (RSA) and ii) non-correlated respiratory (NRSA) ones. RSA is obtained by filtering the \( r \) series by a zero-phase FIR filter, whose transfer function mimic the experimentally measured transfer function between respiration and RR [6]. NRSA is obtained as the output of an AR(3) system, having a dominant conjugate-pole pair placed in the z-plane in such a way to generate a LF oscillation in the output series.

Two noise \( w_t \) and \( w_r \) are added to both \( r \) and \( t \) taking into account possible effect of measurement errors. In particular, level of \( w_t \) was fixed (SNR=25 dB), while \( w_r \) ranged from 140 to -20 dB. The full-band and the sub-band approach are then compared in presence of different noise realizations and SNR values.

IV. Results

Figure 2 (a),(b) and (c),(d) show the results obtained by the proposed sub-band and traditional full-band approach, respectively. Results refer to a SNR = 140dB. Figures show, both in time (a)(c) and in frequency (b)(d) domain, the comparison of simulated wide-band respiratory influence (thin lines) and its estimate (bold line). Traditional approach (Figure 2 (c),(d)) is able to detect the three main components which characterize the simulated influence, but neither the center frequency or the power of each peak may be correctly evaluated. As a result, the time-domain fitting of respiratory activity is not completely satisfactory. Conversely, a more reliable estimation is obtained by using the proposed approach. In this case the estimated RSA more closely fits the simulation values (Figure 2 (a)) and the spectral components of the signal are more precisely identified (Figure 2 (b)). In particular, it is worth noting the correct identification of the lower frequency peak, which is not influenced by the presence of the adjacent LF component in the NRSA generated signals, as it happened for the full-band identification.
Global results are shown in Figure 3, where mean and standard deviation of the errors between actual and estimated time-domain RSA are plotted as a function of different noise levels. WP sub-band identification (bold lines) more precisely estimate the simulated RSA curve: the mean square error (MSE) is lower than in full-band up to SNR=0dB. Only for SNR values lower than 0dB, the two approaches provide comparable results. This is probably due to the ARX identification procedure which is no more able to correctly capture the dynamics of the process buried in noise.

Figure 2 (a),(b) Sub-band identification and WP decomposition: actual (thin line) and estimated (bold line) RSA. Results are compared in time (a) and frequency (b) domain. (c),(d) Full-band identification: actual (thin line) and estimated (bold line) RSA.

Figure 3 Mean square and standard deviation errors between real and estimated RSA. Bold line: Sub-band identification after WP decomposition; Thin line: full-band identification. MSE: Mean square error.
CONCLUSIONS

The proposed algorithm is able to correctly separate RSA from the global RR variability as documented by the results obtained by ad-hoc simulations. In particular, the data evidenced an improved performance in the quantification of RSA when the ARX identification is applied on the set sub-band signals, generated by the WP decomposition algorithm. The more precise quantification of RSA can be usefully employed for the correct analysis of ANS status and sympatho-vagal balance. This is particularly useful when respiratory influence is hardly recognizable on the HRV spectra such as in case of an irregular respiration, which broadens the relevant component, in case of reduced variability or when a very low breathing pushes, without inducing entrainment phenomenon, the respiratory peak close to the LF component on the spectrum.

REFERENCES

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