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Derivation of Frequency Components from Overnight Heart Rate Variability Using an Adaptive Variational Mode Decomposition

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***Abstract*— Heart rate variability (HRV) is a non-stationary, irregularly sampled signal that represents changes in heart rate over time. The HRV spectrum can be divided into four main ranges covering high, low, very low and ultra-low frequencies. The components lying in these bands, both amplitude and frequency modulated, provide valuable information about various physiological processes. The aim of this study was to verify the usefulness of adaptive variational mode decomposition (AVMD) in the extraction of these components from overnight HRV. The effectiveness of this new approach was compared to multiband filtering (MBF) using a synthetically generated signal, as well as real data from three patients. AVMD turned out to be more robust and effective than MBF, particularly in the high and low frequency ranges, making it a reliable method for deriving the HRV frequency components.**

***Clinical Relevance*— The extracted frequency components of heart rate variability provide insight into the regulation of basic physiological processes by the autonomic nervous system.**

I. Introduction

Heart rate variability (HRV) is a signal that represents changes in heart rate (HR) over time. It is defined as the time intervals between consecutive R peaks in the QRS complexes of the electrocardiogram. HR is controlled by the autonomic nervous system (ANS) through two antagonistic subsystems called sympathetic (SNS) and parasympathetic nervous system (PNS) [1]. HRV analysis provides a lot of useful information, such as the state of the ANS, so research on HRV has been going on for decades. The HRV spectrum can be divided into four main ranges. The high frequency (HF) band (0.15-0.4 Hz) mostly represents PNS activity with the vagus nerve and is clearly related to respiration [2],[3],[4],[5]. The low frequency (LF) band (0.04-0.15 Hz) is influenced by blood pressure (BP) through the baroreflex system, PNS and SNS [2],[3],[4],[5]. The very low frequency (VLF) band (0.004-0.04 Hz) is less known. Factors that may affect it include physical activity, thermoregulation, renin-angiotensin system and the internal nervous system [2]. An even less understood range is the ultra-low frequency (ULF) band (<0.004 Hz), most often associated with the circadian rhythm [2],[4],[5]. Summarizing, except well-known relationship between HF and respiratory rhythm, there is a lack of quantitative information of mentioned frequency components. Moreover, it is not even certain which factors actually influence, and to what extent, VLF and ULF. This underlines the importance of a proper method of extracting these components for their further analysis.

HRV frequency analysis is most often performed using the fast Fourier transform or autoregressive modelling [6],[7]. Other popular methods include short-time Fourier transform (STFT) [1],[6] and empirical mode decomposition (EMD), which has been used, among others, to identify the HRV component associated with breathing [8] or to analyze the HF component in fetal HRV [9]. Recently, the effectiveness of extracting frequency components from overnight HRV was tested using multiband filtering (MBF), EMD and STFT on a synthetic signal and real data [10]. Despite the non-stationary nature of the signal, the best results were achieved with MBF. An interesting and effective new alternative to those approaches is the variational mode decomposition (VMD) of a signal into components with distinct frequency characteristics [11]. While it has already been used for ECG or HR, the analysis of the HRV components by VMD has not yet been attempted.

The aim of this work was to test the suitability and accuracy of the adaptive version of VMD in deriving the four frequency component from overnight HRV. A synthetically generated signal and real data were used and the results were compared directly with MBF.

II. Methods

A. Data

In order to directly evaluate the extracted frequency components, a synthetic, non-stationary, 6-hour HRV signal was used, generated in the same way as in [10]. The idea was to simulate the four components (denoted as HFc, LFc, VLFc and ULFc) in a continuous form and sampled at 1 kHz, as both amplitude (AM) and frequency (FM) modulated signals with properties determined from real HRV analyses. Summing them and shifting up by 0.95 s produced a continuous cHRV. Then unevenly HRV distributed in time was created by selecting samples lying on the cHRV, consistent with the relationship between HRV values and the timeline. As the last step, the data was disturbed by adding Gaussian noise.

The real data come from an overnight polysomnographic study of St. Vincent's University Hospital Sleep Disorders Clinic in Dublin available on the PhysioNet platform [12]. The HRV spectrograms of all 25 subjects were analyzed for clear traces of HF and three of them (Patients #5, #7 and #11) were selected as representative data for further work. Of all polysomnographic records, only the ECG signals sampled at 128 Hz were used. For Patient #11, it was necessary to remove the first 54 minutes due to electrode disconnection artifacts.

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B. Multiband Filtering and Adaptive Variational Mode Decomposition

The reference method in this study is multiband filtering (MBF), which has proven to be a more effective one than EMD or STFT [10]. The passband, zero-phase, minimum order FIR filters with a stopband attenuation of 60 dB were applied for HF, LF and VLF components extraction according to their frequency ranges. For the ULF component, an analogous lowpass filter was used.

VMD is one a the newest mode decomposition method. It can decompose a non-stationary signal into several intrinsic mode functions (IMF) with different center frequencies [11]. For this purpose, it uses adaptive Wiener filters and optimization is done with the alternating direction multiplier method. Importantly, this is a non-recursive approach where all searched modes are extracted simultaneously. The final IMFs of a signal $x(t)$ result from minimizing the sum of the spectral widths of all modes:

$$\min_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \frac{d}{dt} \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\}, \quad \text{s.t.} \quad \sum_k u_k(t) = x(t), \tag{1}$$

where u_k stands for the kth mode with its center frequency ω_k, δ is the Dirac delta, and * denotes convolution.

The original VMD procedure, unlike e.g. EMD, assumes an arbitrary set number of searched modes – *maxIMFs*, while it is possible that each of the non-stationary, overnight HRV component contains in its characteristic range several dominant frequencies due to its temporary stabilization. Inadequate setting of this parameter may lead to missing or mixing the searched modes [13]. Therefore, we propose an adaptive VMD (AVMD), aimed at finding the appropriate number of IMFs. It is based on the observation that a justified increase of *maxIMFs* precipitously improves the matching of the IMFs sum to the signal and reduces the residual ε. At the same time, *maxIMFs* should be relatively small to shorten the time needed for the optimization procedure embedded in VMD. In the case of HRV decomposition, the four components are searched, so the algorithm starts with *maxIMFs* = 4, which is then successively incremented. In the ith iteration, the relative energy of ε is calculated in the logarithmic scale

$$\delta_\varepsilon(i) = \ln \frac{\|\varepsilon\|_2}{\|\mathrm{HRV}\|_2} \tag{2}$$

and compared with $\delta_\varepsilon(i\text{-}1)$. If the reduction of $\Delta_\varepsilon = \delta_\varepsilon(i\text{-}1) - \delta_\varepsilon(i)$ is greater than last time, the algorithm proceeds, but if it is not so during three consecutive iterations, the procedure is terminated and the decomposition result associated with the smallest δ_ε forms its final outcome.

C. Hilbert transform

The instantaneous amplitudes and frequencies of the non-stationary HRV components can be derived using the Hilbert transform (HT) [14]. The use of HT on a real component x_c returns the analytical signal X_c which consists of both the original x_c and the imaginary part h_c (HT of x_c):

$$X_c(t) = x_c(t) + jh_c(t) = A_c(t)e^{j\varphi_c(t)}. \tag{3}$$

A_c and φ_c are clearly defined, but the instantaneous frequencies of components (f_c) require additional calculations after φ_c unwrapping:

$$f_c(t) = \frac{1}{2\pi} \frac{d\varphi_c}{dt}. \tag{4}$$

D. Procedure

The suggested optimal ECG sampling rate for analyzing the HRV spectrum is 250 to 500 Hz or even higher [15]. For this reason, each real ECG was upsampled from 128 to 1280 Hz to find R peaks with a resolution better than 1 ms. In the next step, the RR signal was created from the time intervals between successive R peaks. There were distortions in real ECGs due to various artifacts which is common but leads to outliers in HRV. To preserve the original timeline and not to distort the component phases in the rest of the signal, RRs lower than 0.61 s were added to their larger neighbors to form surrogate RRs, and then values above 1.22 s were split into two equal surrogates. The timeline was reconstructed as a cumulative sum of RR intervals and cubic spline interpolation at 10 Hz was used to obtain the uniformly sampled signal. An antialiasing, zero-phase filter with a cut-off frequency of 0.5 Hz was then applied before resampling HRV down to 2 Hz.

In the next step, AVMD was performed to obtain the optimal amount of IMFs. HT was applied for each mode to calculate the instantaneous frequencies and their histograms were generated. Finally, HFc, LFc, VLFc, and ULFc were formed from the sum of all IMFs whose histograms contained most of the counts in the corresponding frequency ranges.

E. Evaluation of the method

The effectiveness of AVMD was assessed on the basis of the similarity of the extracted and actual frequency components of the synthetic HRV. The Pearson coefficient r of correlation between the signals' samples was calculated, as well as the relative error of extraction:

$$\delta_{ex} = \frac{\|x_c - x_s\|_2}{\|x_s\|_2} 100\% = \frac{\|\varepsilon_c\|_2}{\|x_s\|_2} 100\%, \tag{5}$$

where x_c and x_s stands for the extracted and synthetic component, respectively. In addition, the medians of absolute residuals $|\tilde{\varepsilon}_c|$ were calculated, and the one-sided Wilcoxon signed-rank test performed at significance level $\alpha = 0.05$ to check whether $|\tilde{\varepsilon}_c|$ for one method was lower than for another. The above results were confronted with MBF.

Finally, the actual waveforms of the HRV components were extracted from the three patients' data, and then their instantaneous amplitudes and frequencies were computed and visualized together.

III. Results

The effectiveness of AVMD was evaluated by comparing the results of extraction with the known components of the synthetic signal in terms of their instantaneous amplitudes and frequencies calculated using the HT. The reproduced AM and FM retain their real modulation character (Fig. 1).

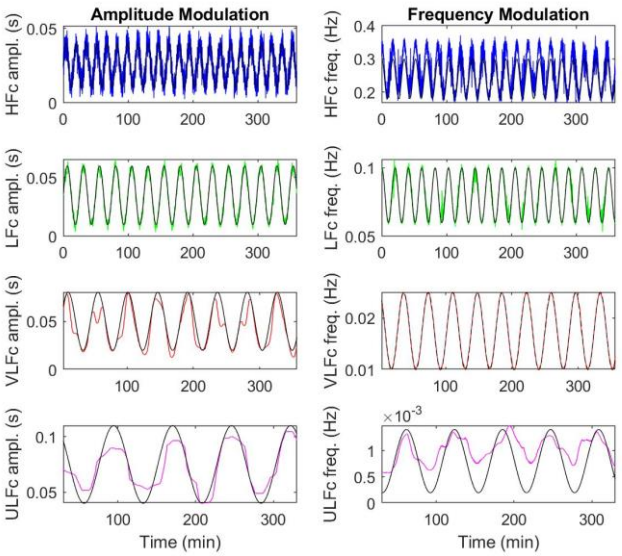

Figure 1. Instantaneous amplitudes (left) and frequencies (right) of the components extracted from synthetic HRV with AVMD (color) against their true traces (black).

The quantitative analysis of the results for AVMD and MBF was summarized in Table I. Both methods have similar accuracy with the advantage of AVMD for HF and LF. However, for VLF and ULF, the MBF turned out to be more precise.

Additionally, the traces of frequency components extracted from the real HRVs (Patient #5, #7 and #11) were visually compared for AVMD and MBF in Fig. 2. The waveforms are nearly identical for both methods, which confirms correct extraction in all cases.

The reproduced AM and FM from clinical data are shown in Fig. 3. Despite the obvious differences between patients, the overall modulation characteristics remain similar.

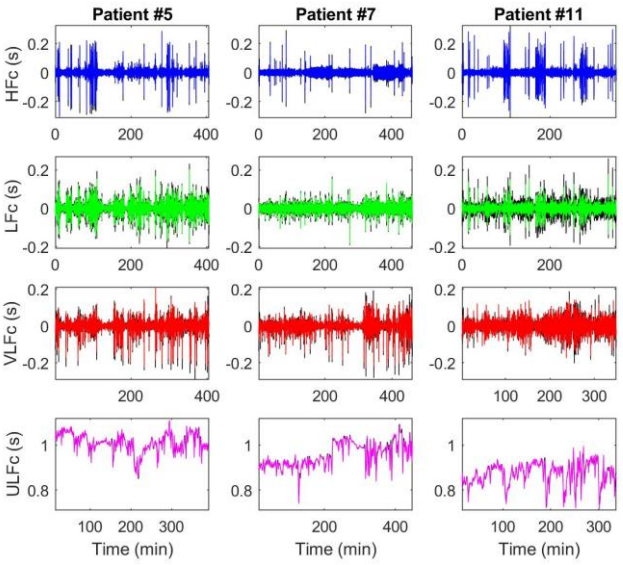

Figure 2. Frequency components extracted from real HRVs using MBF (black) and AVMD (color).

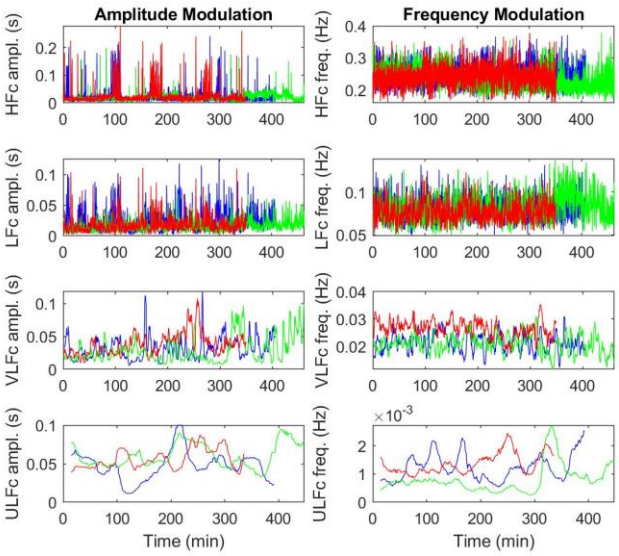

Figure 3. Instantaneous amplitudes (left) and frequencies (right) of the components extracted with AVMD from real HRV of Patients #5 (blue), #7 (green) and #11 (red).

TABLE I. RELATIVE ERRORS (δ), CORRELATION COEFFICIENTS (r), AND MEDIANS OF ABSOLUTE RESIDUALS ($|\tilde{\varepsilon}_c|$)

Component	Method accuracy					
	MBF			***AVMD***		
	δ [%]	r	$\lvert\tilde{\varepsilon}_c\rvert$ [ms]	δ [%]	r	$\lvert\tilde{\varepsilon}_c\rvert$ [ms]
HF	36.0	0.938	4.66	34.2	0.944	4.44*
LF	16.7	0.986	3.00	13.0	0.992	2.40*
VLF	13.0	0.992	0.88*	19.4	0.988	2.24
ULF	0.01	1.000	0.08*	0.71	0.992	1.45

* significantly smaller

IV. DISCUSSION

The aim of this study was to verify the usefulness of AVMD in the extraction of four frequency components from overnight HRV. In determining the effectiveness of the proposed method, we used own synthetic signal instead of the application of the popular integral pulse frequency modulation (IPFM) model [16], since inferring the true physiological drives from the HRV components requires an additional solution of an inverse problem [10]. In this work, the original cHRV was generated from the non-stationary components with known AM and FM, which allowed for a precise analysis of the obtained results.

Because VMD is one of the most modern approaches to signal decomposition, there is still little research on its adaptive implementation. Most of the published algorithms are general in nature and therefore quite complex, e.g., [13],[17],[18],[19]. On the contrary, the procedure proposed in this work, dedicated to HRV decomposition, is very simple. It only takes into account the unevenly decreasing energy of the residual, however performs quite well as shown when decomposing the synthetic signal (Fig. 1).

AVMD turned out to be more effective in the correct extraction of HFc and LFc compared to MBF (Table I). Despite the proper extraction of the VLFc, specific, minor

deviations in the AM may suggest that some part of this range was included in another mode (Fig. 1). All the calculated performance coefficients indicate the advantage of MBF in the case of the ULFc, however, the AM of this band was much better reconstructed by AVMD (Fig. 1) than in the analogous experiment carried out for MBF [10]. This is important because it represents the magnitude of physiological activity. The FM of ULFc also retains its true characteristic, although there is no frequency representation below 0.0005 Hz (Fig. 1). Overall, it seems that AVMD has provided generally more precise information even in the ULF band compared to MBF.

Extracted components from real HRVs were extremely similar in the case of both, completely different methods, which only confirms the correctness of the extracted components. When comparing the methods, it should also be emphasized that MBF requires a priori knowledge of the frequency ranges of the components sought. This information is not so important in the case of a VMD, where the algorithm itself looks for separate IMFs in the signal. The problem of selecting the number of searched modes has been successfully solved by the adaptive version of VMD based on residual analysis, making the new approach not only more effective than MBF but also more robust due to the lighter restrictions on components belonging to the frequency bands.

The presented methodology has some limitations. The main one is that the IMFs from AVMD have been combined, accepting the well-established frequency ranges of the expected four physiological components. It should be also noted that the extracted frequency components do not directly reflect physiological drives, but the impact of ANS activity on final HRV. In addition, the influence of ECG artifacts on the algorithm efficiency was not investigated and the method was tested on only three real signals.

V. Conclusion

The AVMD's overall performance in the overnight HRV component analysis is better that MBF, as well as EMD and STFT. Only in the case of VLF, MBF was clearly more effective. In the case of ANS analysis, the most important and most frequently studied bands are HF and LF, for which AVMD definitely outperforms the other analyzed methods of frequency component extraction. Summarizing, the derived components along with their AM and FM are reliable in a qualitative and quantitative manner, both when analyzing real HRVs and in comparison with the ground truth – a synthetic signal.

In addition, the FM of the real components obtained from AVMD fell into the standard four frequency ranges. This only confirms the compliance of the results with the bands defined in the literature.

Future work will focus on the reconstruction of internal ANS drives from the extracted components using the IPMF model. Based on the satisfactory results of AVMD, it is also worth trying to implement this approach in online analysis.

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