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Analysis and processing of heart rate variability by time-frequency representation: quantification of the pedaling frequency modulation

Olivier Meste, member *IEEE*, Gregory Blain and Stephane Bermon

***Abstract*— It has been shown that a pedaling frequency component can be extracted from the heart rate variability (HRV) signal using a time-varying filter. It is shown that this filter can be implemented directly in the time-frequency plane with different approaches. The need of resampling the data is also discussed with regard to the artifacts produced when the shanon condition is not fulfilled. In order to interpret the similar amplitude profiles of the pedaling component for untrained and trained subjects, an attempt for the model parameters setting is proposed. Consistent results on a large data set illustrate the feasibility of such processing.**

I. INTRODUCTION

In [1], it has been shown for the first time that during cycling exercise the Very High Frequency band from the Heart Rate Variability (HRV) corresponds to a pedalling component. This observation has been recently confirm with a larger set of subjects and for three different pedaling frequencies [2]. A model has been proposed to explain how and why departing from ideal experimental conditions, where the right and left legs muscles contract in pure opposite phase, the amplitude of the fundamental frequency could be greater than its harmonics. In summary, it is explained by the presence of asymmetry and delay between right and left leg muscles contractions. Assuming that the HRV signal is mechanically modulated by an oscillation in venous blood flow during intense exercise it is expected to find a close relationship between the pedaling frequency component and the exercise workload (the higher the workload, the greater is the muscle contraction contribution to venous return). This hypothesis is not in accordance with our previous results [1] which demonstrated no significant amplitude differences in the pedaling frequency modulation between untrained subjects and athletes, although the maximal workload achieved during the test was significantly and substantially higher in athletes. The aim of this paper is to fully explain how the linear time-frequency representation that is the Short Time Fourier Transform (STFT) is used not only to analyse but also a to process the signal. In addition, a simulation will show that changes in the parameters of the pedalling model could explain our findings, providing a full simulation framework where the modulation model is also accounted. [3]. Finally, the processing of a large set of real data will illustrate our findings.

O. Meste is with the Lab. I3S UNSA-CNRS, University of Nice-Sophia Antipolis, France meste@i3s.unice.fr

G. Blain is with Laboratoire de Physiologie des adaptations, Performance motrice et Sante, University of Nice-Sophia Antipolis, France blain@unice.fr

S. Bermon is with the Monaco Institute of Sports medicine, Monaco, bermon@unice.fr

II. TIME-FREQUENCY ANALYSIS AND PROCESSING

Spectral analysis techniques, such as the Fourier transform or autoregressive modeling, have been the most extensively used methods to quantify HRV [4][5]. Although under stationary conditions the quantification of the spectral domain is a simple task, during dynamic exercise condition, the variation of the spectrum frequencies and of their relative amplitude makes it more challenging. In [3], we showed that using a time-varying approach, both time-varying frequencies and amplitudes can be estimated from the R-R intervals series recorded during maximal and graded exercise. In [7], we used this signal processing method to demonstrate a linear relationship between the amplitude of respiratory sinus arrhythmia (RSA) component in HRV and ventilation during intense exercise. In this study, the amplitude was measured using a time-varying filtering. Among the available time-frequency representation, one the main advantages of the STFT is to be linear and thus to allow a direct implementation of a time-varying filter [3]. Although in this application only the envelop is quantified, additional information can also be obtained from the filtered signal. It is well known that the STFT has a limited time-frequency resolution. However, not only this resolution is sufficient in our application, but also the STFT has the advantageous to be less sensitive to interferences such as cross-term interference, that are known to distort the analysis process [8]. If other time-varying approaches, such as the Wavelet, are better adapted to signals that contains transient events at different scales, the STFT is fully adapted to time-varying spectral lines quantification [8].

From the ECG signal sampled at a 1000 Hz rate, the heart period signal $hp(k)$ was calculated as the difference $hp(k) = t_k - t_{k-1}$ where t_k is the occurrence time of the kth beat. The signal $hp(k)$ was separated in two components: the trend $po(k)$ and the variability $m(k)$. This separation was obtained by using a low-pass filter. We can get rid of the filter design difficulty by computing directly from the short-time Fourier transform (STFT) the quantity:

$$R(k) = \sqrt{\frac{1}{K} \sum_{f=f_{obs}(k)-\delta}^{f_{obs}(k)+\delta} |M(k,f)|^2} \qquad (1)$$

with $f_{obs}(k)$ the time-varying frequency of interest. $M(k,f)$ is the STFT of the R-R intervals variability as defined in [3]:

$$M(k,f) = \sum_u m(u)h(u-k)e^{-j2\pi\frac{\ell}{K}u} \qquad (2)$$

with $-K/2 \leq \ell \leq K/2-1$ integer and $f = \ell/K$

The analysis window $h(u)$ was energy normalized. In our application, aiming to quantify a pedaling frequency component (PFC) in HRV, the value of the parameter δ was set $\pm$ 0.1Hz around the imposed pedaling frequency.

A time-varying filter design is required when one consider the analysis of the filtered signal. Using the frequency $f_{obs}(k)$ we define a binary template or filter $G(k,f)$ in the time-frequency plane such that:

$$G(k,f) = \begin{cases} 1 \;\; for \;\; |f| \in [f_{obs}(k) - \delta; f_{obs}(k) + \delta] \\ \\ 0 \;\; for \;\; |f| \notin [f_{obs}(k) - \delta; f_{obs}(k) + \delta] \end{cases} \tag{3}$$

The selectivity of the time-varying filter $G(k,f)$ depends on the value δ previously defined. The filtered signal $x(k)$ was then obtained using the Inverse Short Time Fourier Transform applied on the modified $M(k,f)$ such that:

$$x(k) = \frac{1}{K} \sum_{u} \sum_{\ell=-K/2}^{K/2-1} G(u, \frac{\ell}{K}) M(u, \frac{\ell}{K}) h(k-u) e^{j2\pi \frac{\ell}{K} k} \tag{4}$$

Note that the time-varying filter $G(k,f)$ has to be designed taking into account the negative frequency part. The filtered signal $x(k)$ being a narrow band signal, we used the Hilbert transform in order to extract the envelope $A(k)$ of the signal, which is defined as the modulus of the analytical signal:

$$\tilde{x}(k) = x(k) + j\mathcal{H}[x(k)] = A(k) e^{j\varphi(k)} \tag{5}$$

where $\mathcal{H}[.]$ stands for the Hilbert transform.

Moreover, although the frequency of interest, i.e. the pedaling frequency f_p, was maintained constant in the continuous time domain in our experimental setting, this frequency became time-varying when extracted from in the heart period signal such as:

$$f_{obs}(k) = po(k) f_p \tag{6}$$

where $po(k)$ is the trend (or instantaneous mean heart period) of the heart period. In our previous studies, we used a maximal and graded exercise test to evidence the pedaling frequency modulation on cardiac activity. Because of the workload increase, the quantity $po(k)$ vary with time and so forth for the observable pedaling frequency.

It should be mentioned that the shanon criteria apply for this observation because the continuous pedaling signal is sampled at the R-wave occurrence with a time-varying sampling period ($\approx po(k)$). This criteria imposes the sampling frequency (the inverse of the sampling period) to be twice the maximum frequency f_{max} of the continuous observation. If this condition is not fulfilled, the spectrum that lies in the frequency band greater than half the sampling frequency duplicates in a frequency band lower than half the sampling frequency. This phenomenon can mislead the interpretation and quantification of the spectrum. For instance, for a pedaling rate of 70 rpm the spectrum is free of aliasing when $po(k)$ (the mean heart period) is lower than 430 ms (heart rate higher than $\pm$ 140 bpm). For a pedaling rate of 90 rpm, the limit is more drastic because $po(k)$ has to be lower than 330 ms (heart rate higher than $\pm$ 180 bpm). In case of aliasing, the interpretation of results can be misled when the duplicated pedaling frequency is superimposed to another one, such as the RSA component.

This aliasing affect has also an impact on the resampling of the variability signal ($m(k)$). In accordance with the PFM model [3], an ECG signal has been synthesized with a constant amplitude sinusoidal variability in the R waves position with a frequency equal to 1.17Hz. This frequency corresponds to a pedalling rate of 70rpm. After processing this ECG, the computed $hp(k)$ was filtered, providing the variability signal $m(k)$. In Fig. 1 and Fig. 2 the magnitudes of the STFT are shown for the resampled and the unevenly sampled $m(k)$, respectively. The resampling technique was based on a well-known spline interpolation at a sampling frequency equal to 3Hz.

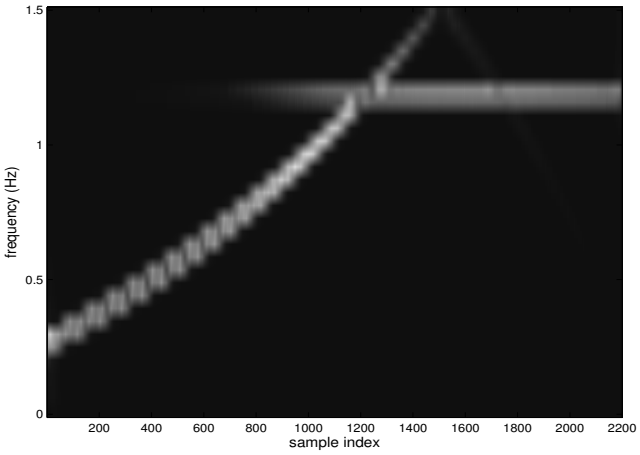

Fig. 1. Amplitude of the STFT of the synthesized variability signal. The signal has been resampled with spline functions at a frequency rate equal to 3 Hz

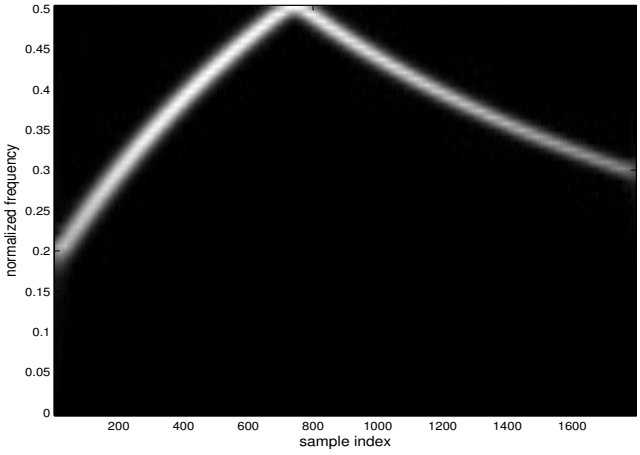

Fig. 2. Amplitude of the STFT of the synthesized variability signal. The signal wasnt resampled but unevenly sampled

In these representations, because the frequency of the modulation is constant, one could expect a straight line at least for the resampled signal. This is because in the samples

interval [0-1200] of Fig. 1 the resampling was applied to an aliased frequency. As well for Fig. 1, Fig. 2 doesn't exhibit straight lines because the constant frequency of the modulation (i.e. the pedalling effect) is sampled with a time-varying sampling frequency. In this figure, the intervals [0-750] and [750-1800] corresponds to the aliased and non-aliased frequency, respectively. Apart from the complex description of the time-frequency content, it is noticeable that the time-frequency representation of the resampled signal exhibits artifacts around the index 1200. This shows that the spline interpolation distort the frequency content, especially close to half the sampling frequency. This remark led us to use the unevenly signal for the processing and analysis of the variability.

III. Observation Models

An important point is the significance of the estimated amplitude (1). In the previous simulation, the PFM model proposed in [3] has been used to generate the ECG. It has been demonstrated that when the PFM model is used, the estimated amplitude should be corrected by using the formula:

$$c(k) = \pi \frac{R(k)}{po(k) sin(\pi f_{obs}(k))} \tag{7}$$

The results plotted in Fig. 3 illustrate the interest of such correction. Because in the simulation the modulation had a constant amplitude it is expected to retrieve from the variability signal a constant magnitude. From Fig. 3 it is clear that the observation model affects the estimated amplitude (dashed line) and that assuming the appropriate model selection and correction, the extracted amplitude can be corrected (solid line). Note that the notch at the sample index 750 appears when the frequency cross half the normalized frequency (0.5).

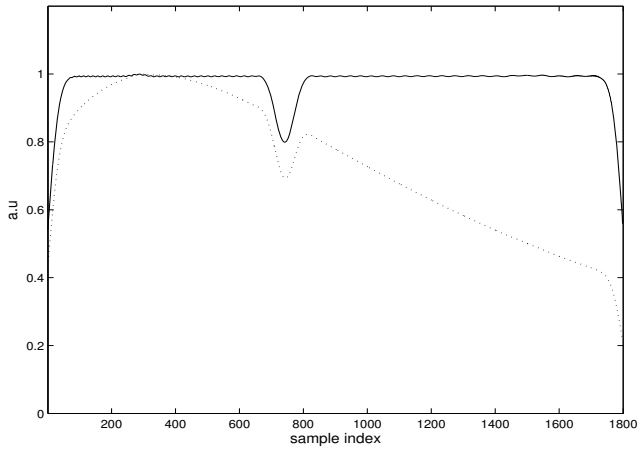

Fig. 3. The quantity $R(k)$ directly computed from the STFT of the variability signal. The uncorrected (dashed line) and corrected (solid line) were normalized for comparison purpose

In the next simulation, we compared the amplitude of the fundamental frequency (proportional to the square root of the power spectral density) with two different sets of parameters corresponding to an athlete and an untrained subject. From [1], the quantity of interest is:

$$Y = K \sqrt{\frac{1 - 2\alpha_1 cos(2\pi dr_1/100) + \alpha_1^2}{1 - 2\alpha_2 cos(2\pi dr_2/100) + \alpha_2^2}} \tag{8}$$

where K is the ratio of the amplitudes from the untrained and athlete, α is the legs asymmetry coefficient, dr is the delay normalized by the pedalling period (percentage) relative to the opposite position of the two legs, subscripts 1 and 2 stands for the untrained subject and athlete respectively. From (8), it is clear that comparing these subjects with two different physical characteristics is difficult because of the dynamic profile of the parameters involved in the pedaling frequency modulation (see above). As previously mentioned, we synthesized two ECG and generated two variability signals for the athlete and untrained subject, respectively. The corrected estimated amplitude (7), i.e. the amplitude of the sum of the two legs contribution, during a simulated graded exercise, is shown in figure 4 for both the virtual athlete and untrained subject. The parameters used in this stimulation were set to the following values: a random delay with an increasing mean from 1 to 2 % of the pedalling period (equal to 90 rpm), an asymmetry coefficient increasing from 0.95 to 0.8, a linear increase of the effort magnitude, for the athlete; a random delay with an increasing mean from 1 to 5 % of the pedalling period (equal to 70 rpm), an asymmetry coefficient increasing from 0.95 to 0.7, a linear increase of the effort magnitude half the values of the athlete, for the untrained subject. The influence of the pedaling rate and the fatigue on the asymmetry coefficient is discussed in [9]. The proposed variations are supposed to account for the difference of pedaling rates and the duration of the graded exercise. Note that a random variability has been added in order to add some physiological fluctuation into the observation.

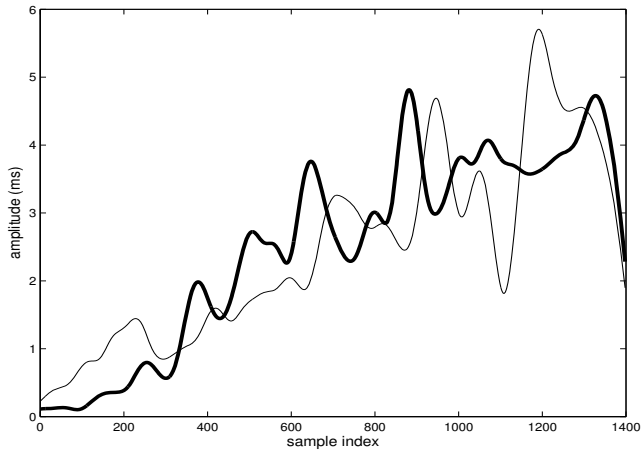

Fig. 4. The amplitude of the synthetic pedalling signal that mimic the blood flow oscillation for the athlete (thick line) and the untrained subject (thin line)

As it will be mentioned in the next section, all subjects exhibited a continuously increasing estimated amplitude

disregard their training conditions. In order to discard any hypothetical bias due to the time-frequency processing, a monte-carlo simulation has been conducted over 100 trials. For each trial a noisy ECG has been synthesized without pedalling interferences. The corresponding envelop has been estimated supposing that a 90 rpm pedaling interference is present. Applied to the HRV signal computed from the synthesized ECG, one STFT result is given in fig. (5) where the simulated respiration component is visible. In fig. (6), the average of the 100 estimated envelops is shown where it appears that the mean envelop is flat and not increasing. The pic at time index 325 is due to the respiration component that lies in the expected pedaling frequency bounds (see white dashed lines in fig. (5) corresponding to the filter template). This simulation confirms that the visible positive trend of the pedaling envelop is not due to the estimation process.

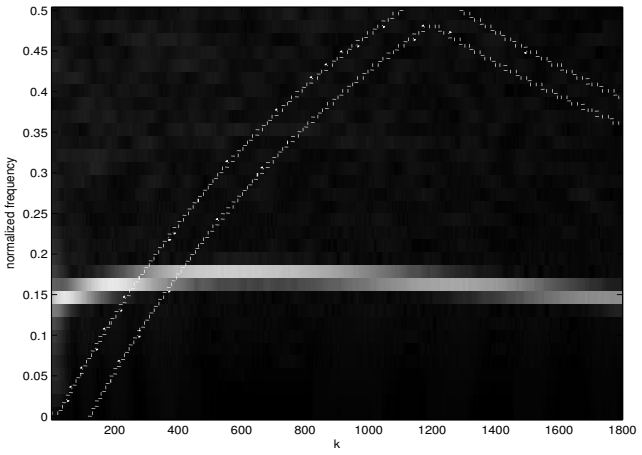

Fig. 5. Magnitude of the short time fourier transform of one realization of the noisy respiration (pedalling signal not added)

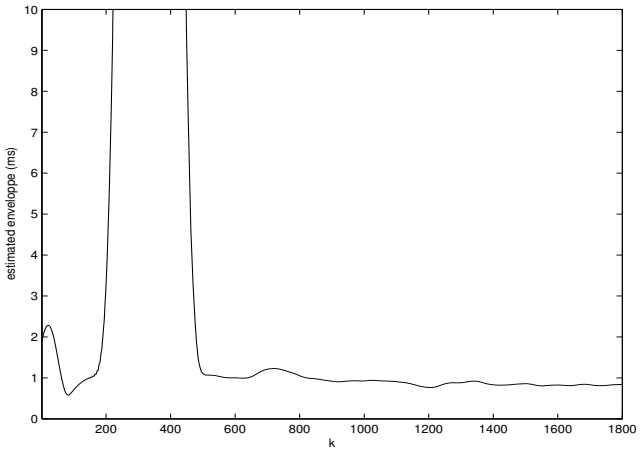

Fig. 6. Average of the estimated envelop of the pedalling signal from the 100 noisy respiration signals (pedalling signal not added)

IV. Application to real data

To illustrate the use of such approach, 15 subjects with different training level from sedentary to elite athletes have been studied. This set has been clustered into three groups of 5 subjects corresponding to three different pedaling frequency: 70 (mostly sedentary), 80, 90 (mostly elite athletes) revolutions per minute (rpm). Because the difference between corrected and uncorrected was not significant, the estimated amplitude was provided without correction (7), allowing a measurement in millisecond. In order to avoid the interference between the respiratory sinus arrhythmia component and the pedaling component, results are display from 55 to 100% of the maximal power output P_{MAX}. In Fig. 5 in [2], note that in all groups, the estimated amplitude of the pedaling component continuously increased with workload up to the maximal workload without any significant differences between groups.

V. Conclusion

Heart rate variability is strongly linked in a complex way to the activity of autonomous nervous system. In addition to this neural modulation, mechanical events involving respiration or locomotion (muscle pump) via oscillation in the venous return to the heart may also influence this variability. In this study we focused our attention on the pedaling frequency modulation. Because its contribution to the total variability is not stationary, a time-varying approach was necessary to quantify this modulation. In this work, we showed here that the STFT can be used not only for the analysis process but also for filtering the signal. Based on the ad-hoc setting of the pedaling model parameters, we successfully used this approach to extract the dynamic pattern of the pedaling frequency modulation from simulated and real signals. Future works will concern the design of experimental protocol to check the accordance of the parameters value selection.

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