Hysteresis Analysis of the PR-PP relation under Exercise Conditions

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Abstract

This work aims to analyse the link between PR and PP intervals under maximal and graded exercise test as well as under pyramidal exercise where the effort is not released abruptly. After defining two classical P waves processing, we propose a new criteria to evaluate the quality of the intervals estimation. Both in simulation and real cases, we show that the preprocessing based on polynomial fitting gives better results. The main output of this global processing is the enhancement of an hysteresis effect in the studied relation.

1. Introduction

The heart period variability, usually analyzed by using the RR intervals, is in fact a variation over a trend or time-varying mean period. Almost all studies are focused on this variation mainly because of the involved protocols which are based on stationary conditions or briefly non stationarity. This is not the case in ECG recording during graded exercise where the characteristics of both the trend and the variability of the heart period are varying. The analysis of the RR or PP trends and the variability can be performed in order to evaluate the sympathetic-parasympathetic balance but also to address the problem of the atrioventricular conduction time variation understanding when it is related to the PR intervals. On the contrary to [1], [2], [3] we only focused on the trend of the heart period whereas its variability, mainly related to the respiration, was not taken into account. In [4], authors have investigated the relation between the PP intervals and the atrioventricular conduction time (and hence PR interval length) in the mean sens which corresponds in this case to use the trends of these intervals but not their variability. We will try to show in this paper that in addition to some paradoxical behavior due to cardiac memory [4], it exists a non linear relation between the PP and PR intervals during graded exercise which exhibits a hysteresis shape.

The major difficulty is to measure accurately the time occurrence of the P waves since with this extremal conditions the signal to noise ratio is poor, the ECG envelope and baseline are modulated by breathing, P waves are very close to R waves and T waves become superimposed to P waves. This challenging measurement will be achieved by using the cross-correlation technique that could be biased by the presence of the breathing baseline. In order to reduce this bias, two P wave pre-processing will be compared: high pass filtering and order one polynomial removal. In order to evaluate the quality of the time of occurrence estimations regards to the pre-processing, we will use a criteria based on the energy of the mean P wave. This criteria will lead us to select the second pre-processing as being more adequate providing P wave time of occurrences used to evaluate the successive PR and PP intervals. Applied on a reduced set of healthy subjects, we will show that the relation $PR = f(PP)$ is continuously linear in the increasing effort and in the recovery stages, both in pyramidal and maximal and graded tests. The hysteresis patterns will be clear when comparing the parameters of the linear relations where the proportionality coefficients and the offsets are different from the increasing effort to the recovery.

2. Methods

The global processing can be decomposed in several sequential stages: R waves detection, P waves pre-processing, P waves detection, evaluation of the time detections. The R wave times of occurrence t_k are estimated applying a threshold technique on the high-pass filtered and demodulated ECG. Then segments including the expected P waves and the corresponding R waves are formed time locked on the t_k. The method chosen for the estimation of the PR_k intervals is the cross-correlation introducing a reference or template P wave. This template will be the mean of a reduced set of successive P waves recorded at the beginning of the exercise. The time interval separating this template and the end of each segment previously formed will be unknown and defined as K.

Then, the time delay d_k corresponding to the time lag of the cross-correlation maximum for each segment will give the corresponding intervals $PR_k = K - d_k$.

It is important to note that this interval do not necessary correspond to peak to peak interval neither to the one defined by using the P wave onset. During high intensity exercise the P wave onset measurement is not reliable because of the superimposed T wave and the P wave peak location could be influenced by the shape changing, as mentioned in [2]. It is easy to calculate the PP_k from the t_k and the d_k by using the expression:

$$\begin{aligned} PP_k &= t_{k+1} - t_k + PR_k - PR_{k+1} \\ &= t_{k+1} - t_k + d_{k+1} - d_k \end{aligned} \quad (1)$$

Unfortunately, even if this time delay estimator provide reliable results it is biased by the presence of a baseline corresponding to the breathing and other artifacts. We propose two baseline removal approach:

A. high pass filtering using a 500th order FIR filter designed with a hamming window and a cut off frequency equal to 5 Hertz
B. order one polynomial substraction fitting the ending 5 samples (E5) of the S wave attached to the kth QRS complex and the beginning 5 samples (B5) of the Q wave attached to the $k+1$th QRS complex. This removal will be performed for all the segments. Assuming that the time definitions of E5 and B5 are invariant with exercise, E5 and B5 will be visually determined on the mean S and Q waves.

In order to evaluate the quality of the d_ks estimation we propose to align all the P waves expecting a residual jitter due to the uncertainty inherent to any time delay estimation. The proposed criteria is based on the energy of the mean P wave as developed below.

Assuming that delayed signals are observed as following:

$$x_i(t) = w_i s(t - d_i) + n_i(t) \quad (2)$$

The ensemble mean is expressed as:

$$m_1(t) = \frac{1}{K} \sum_{i=1}^{K} x_i(t) \quad (3)$$

when the number of observed signal is large enough and that the random variables w and d are independant, this relation can be expressed as:

$$m_1(t) = \int \int w s(t - a) p_D(a) p_W(w) da dw \quad (4)$$

with $p_D(a)$ and $p_W(w)$ the probability densities of the delays and the weighting factor. Then, the mean is:

$$m_1(t) = \bar{w} \int s(t - a) p_D(a) da \quad (5)$$

When calculating the energy of the mean signal V as:

$$V = \int m_1^2(t) dt \quad (6)$$

and assuming that in each observation x_i the signal $s(t)$ is completely observed, the integral is:

$$V = \bar{w}^2 \int \int p_D(a) p_D(b) R_{ss}(a - b) da db \quad (7)$$

where $R_{ss}(\tau)$ is the temporal cross-correlation function defined as:

$$R_{ss}(\tau) = \int s(t) s(t + \tau) dt \quad (8)$$

Using the definition of the characteristic function $\phi_D(u)$ such as:

$$p_D(a) = \int e^{-jua} \phi_D(u) du \quad (9)$$

and $\hat{R}_{ss}(u)$ the Fourier transform of $R_{ss}(t)$, it can be shown that (7) is:

$$\bar{w}^2 \int \int p_D(b) \phi_D(v) \hat{R}_{ss}(v) e^{-jvb} dv db \quad (10)$$

which can be reduced to:

$$\bar{w}^2 \int \phi_D(v) \phi_D(-v) \hat{R}_{ss}(v) dv \quad (11)$$

The probability density being real, the property $\phi_D^*(u) = \phi_D(-u)$ is verified, giving:

$$V = \bar{w}^2 \int |\phi_D(u)|^2 \hat{R}_{ss}(v) dv \quad (12)$$

The cross-correlation being semi-definite positive, its Fourier transform $\hat{R}_{ss}(u)$ is then non negative and even. This implies that:

$$V = 2\bar{w}^2 \int_0^\infty |\phi_D(v)|^2 \hat{R}_{ss}(v) dv \geq 0 \quad (13)$$

Assuming the normal law $\mathcal{N}(m, \sigma)$ for $p_D(a)$, its characteristic function is:

$$\phi_D(v) = e^{jmv - (1/2)\sigma^2 v^2} \quad (14)$$

which implies for V:

$$V = 2\bar{w}^2 \int_0^\infty e^{-\sigma^2 v^2} \hat{R}_{ss}(v) dv \quad (15)$$

The derivative of V regards to σ gives:

$$\frac{d}{d\sigma} V = -4\bar{w}^2 \sigma \int_0^\infty v^2 e^{-\sigma^2 v^2} \hat{R}_{ss}(v) dv \quad \leq 0 \quad (16)$$

Then if the jitter variance decreases the criteria V increases. Considering that after the alignment process the probability density of the residual delays could change its shape, if the function $|\phi_D(v)|^2$ can be approximated by a gaussian law such that:

$$|\phi_D(v)|^2 \approx e^{-\sigma^2 v^2} \;\; pour \;\; v \in \Omega \qquad (17)$$

with Ω the support of $\hat{R}_{ss}(v)$, then when V increases it means that the variance, i.e. the alignment error, has been reduced. This approximation is more accurate when the variance of the random variable D is small and that the signal is low frequency. Theoretically, the use of the variance integral in (6) should be more appropriate and would generalize the results obtained in [5]. Unfortunately, the baseline forming the larger part of the noise prevent us to use this latter approach because of its dependency with the residual delays. Note that the mean P wave m_1 will be obtained using the original P waves rather than the preprocessed ones since the pre-processing will influence the delays estimation performance.

3. Simulation

The aim of this simulation is to illustrate the global processing of the ECG. It is shown in Fig.1 a portion of a synthesized ECG whose envelope and baseline are modulated by a synthesized respiration function and where the TP, PR and RR intervals are time-varying. All the individual time variations include a decreasing trend and a variability added to this trend related to the respiration. The two pre-processing will be compared using this signal supposed to mimic a real ECG during an exercise load increase. We find in Fig.2 the d_ks estimated with the

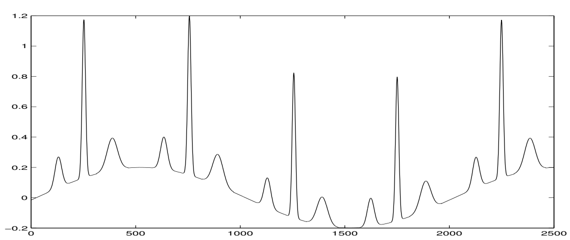

Figure 1. Synthesized ECG

two pre-processing methods compared to the real ones. Polynomial approximations have been plotted in order to focus the comparison on the trend rather than the variability. In this case the variability is sinusoid like within the range [-5,+5]. It is clear that the result from the pre-processing **A** exhibits much more bias than **B**. This visual inspection is completed by the application of the proposed criteria where the value V is 1.1263 for **B** and 1.1220 for **A**. These values must be compared to the not aligned case where V equal to 1.0054, proving that the estimation of the d_ks has been performed correctly with an improvement with **B**. The difference between the V values

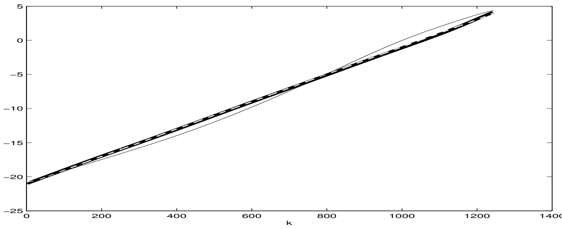

Figure 2. Comparison of the polynomial approximation of the real (white dashed line) d_ks and the estimated ones with pre-processing **A** (thin line) and **B** (thick line)

are very small but as it will be shown in the following it leads to the enhancement of hidden non linearity such as hysteresis.

4. Application

In this application, two young healthy male subjects (P_1 and P_2) performed, on a cycle ergometer, a pyramidal exercise test (PYR) or a maximal and graded exercise test (MG). P_1 participated to PYR only whereas P_2 performed both exercise tests, on two separate days. After a 5 min. warm-up session, PYR consisted of a 8 min. ramp load increase from 60% to 100% $\dot{V}$O2max, immediately followed by a 8 min. ramp decrease from 100% to 60% $\dot{V}$O2max. In the case of the MG, when the subject was exhausted, the effort was released abruptly. We will find in Fig. 3, 4, 5 the heart period $RR_k = t_{k+1} - t_k$ for P_1-MG, P_2-MG, P_2-PYR, respectively. In Fig. 6, 7, 8, 9 we find the plots of $PR_k = f(PP_k)$ for P_1 and P_2 after the pre-processing **A** and **B** where the PR_k intervals have been approximated by a 10th order polynomial. Comparing Fig.6 and 7, the hysteresis relation is more visible after applying **B** what will be the case for others examples. The alignment criteria V for the original (ori) and preprocessed (A,B) P waves are $V_{ori}(P_1, MG) =$ 15.85, $V_A(P_1, MG) =$ 17.46, $V_B(P_1, MG) =$ 17.53, $V_{ori}(P_2, MG) =$ 17.52, $V_A(P_2, MG) =$ 19.98, $V_B(P_2, MG) =$ 20.08, $V_{ori}(P_2, PYR) =$ 23.75, $V_A(P_2, PYR) =$ 24.55, $V_B(P_2, PYR) =$ 24.68. Meaning that whatever the subjects and protocols the pre-processing **B** gives a better alignment.

5. Conclusion

We have proposed a methodology whose aim was to investigate the relation between PR and PP intervals. The use of a polynomial based baseline removal and a criteria for the evaluation of the intervals estimation has permitted

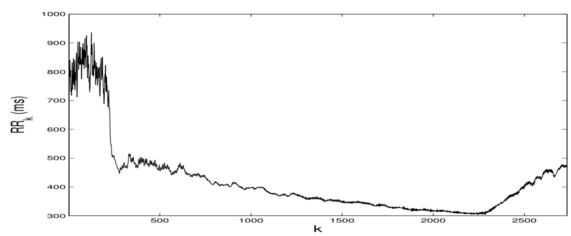

Figure 3. The RR_k intervals during MG test for P_1

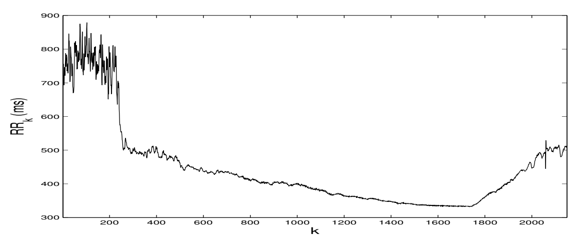

Figure 4. The RR_k intervals during MG test for P_2

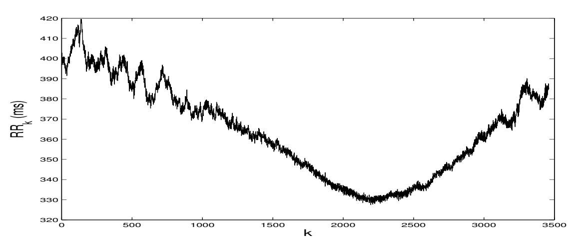

Figure 5. The RR_k intervals during PYR test for P_2

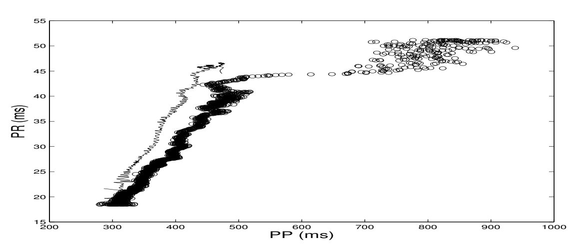

Figure 6. $PR_k = f(PP_k)$ during MG test for P_1 preprocessed with **B**. ∘ and — for ↗ and ↘ effort.

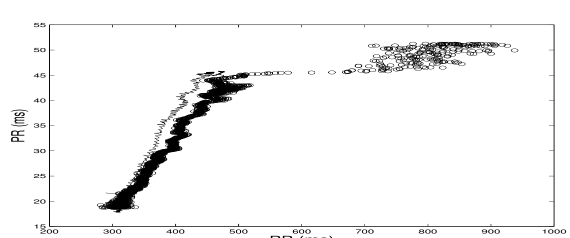

Figure 7. $PR_k = f(PP_k)$ during MG test for P_1 preprocessed with **A**. ∘ and — for ↗ and ↘ effort.

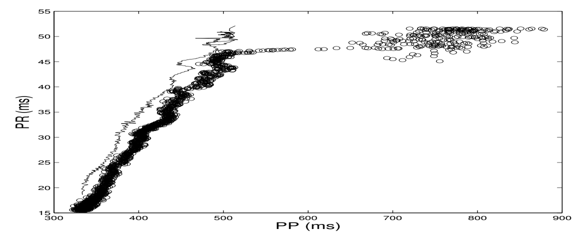

Figure 8. $PR_k = f(PP_k)$ during MG test for P_2 preprocessed with **B**. ∘ and — for ↗ and ↘ effort.

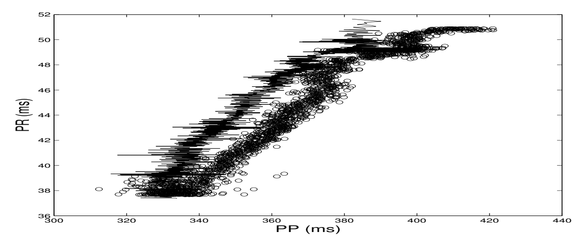

Figure 9. $PR_k = f(PP_k)$ during PYR test for P_2 preprocessed with **B**. ∘ and — for ↗ and ↘ effort.

us to achieve this task. In spite of a very small number of subjects, we evidenced the presence of hysteresis effect in relation with the scope of this work. This hysteresis could attest for the vagus influence on atrioventricular conduction, associated with exercise intensity decrease.

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