Estimation, Analysis and Comparison of the PR and RR Intervals under Exercise Conditions and Recovery

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Abstract

Very little works have been done on PR intervals, undoubtedly because this signal is difficult to extract and process, as in exercise tests where T-P fusion occurs during higher heart rates, what makes this problem still interesting. The common approach for the estimation of PR interval during both exercise and recovery is to determine the latency using the detection of the maximum of cross correlation function. This work aims to present a new method of time delay estimation with unknown signal based on an iterative Maximum-Likelihood approach which generalizes the well known Woody's method. This leads to a new approach to determine the PR intervals taking into account the presence of the T wave that is modeled. This work exhibits the existence of an abrupt change of slopes of PR and RR intervals at the same time occurrence and a phenomenon of "overshoot" during the recovery for athletes.

1. Introduction

The analysis of the heart period series is a difficult task especially under graded exercise conditions. Correlation techniques are usually used to estimate the PR by determination of the latency using the detection of the maximum of the cross correlation [1],[2]. Here, we will present a new approach to determine the PR interval taking into account the presence of the T wave which is especially difficult to extract during high rates because it overlaps the P wave. In order to estimate the PR intervals, we will use the Maximum Likelihood Estimator (MLE). The idea behind maximum likelihood parameter estimation is to determine the parameters that maximize the probability of the sample data.

The first part of the paper is devoted to present a new method to determine the PR intervals. We will present a method which formalizes the Woody's one [3], using an iterative MLE to estimate delays which correspond to PR intervals. We will extend the Woody model because in exercise tests T-P fusion occurs during higher heart rates. It will be based on the modeling of the T wave which overlaps the P wave especially during the exercise, in order to generalized more over. Finally, the results of this new method will be presented: a high correlation between the time occurrence of the abrupt change of slopes of PR and RR intervals during recovery is displayed. Besides, the results exhibit a phenomenon of "overshoot" during the recovery for athletes.

2. Methods

Charles D. Woody [3], presented in 1967 an adaptative filter which allowed identification and analysis of variable latency signals and the basis of detection of latency by correlation. He calculated the cross correlation between each sweep and a template. Hence, the time lag matching the cross correlation maximum corresponds to the latency shift of the given sweep. However, as shown in [4], this method is suboptimal. Actually, in this model, $x_i(n)$ represents all the observations (for all n) of the considered i^{th} PR interval ($i = 1..I$, I the number of realizations). Also $s_{d_i}(n)$ is defined as the reference wave, the template, delayed of d_i as $s_{d_i}(n) = s(n - d_i)$ and $e_i(n)$ a observation's noise:

$$x_i(n) = s_{d_i}(n) + e_i(n) \qquad (1)$$

The technique derives from iterative correlation and averaging of the data signals. In the beginning, a template data block is built. At each step i, the maximum of cross correlation between the template and the i^{th} block gives the estimation of delay $\widehat{d}_i$. When all the $\widehat{d}_i$ for $i = 1..I$ are estimated, each i^{th} data block is corrected by his i^{th} delay $\widehat{d}_i$. The average of these aligned data blocks gives a new template. Then, a new iteration for i from 1 to I is computed to determine the new $\widehat{d}_i$ until convergence.

This method is suboptimal because the considered signal is included into the average taken as a template in the cross correlation step. So, the cross correlation is biased. Also, the same template is used to estimate all the delays during one iteration ; all the estimated delays are taking into account in averaging process at the end of the iteration.

Later, Pham et al. [5] studied the estimation of variable latencies of noisy signals. Jaśkowski and Verleger [6] refereed to a more general model in which the amplitude variability is also allowed :

$$x_i(n) = \alpha_i.s_{d_i}(n) + e_i(n)$$

However, these two studies, [5], [6], are not really fair regards the optimality of the method since they include frequency a priori in their approach.

As in exercise tests T-P fusion occurs during higher heart rates, we can consider that the T wave is represented by a function $f(n;\underline{\theta}_i)$ linearly parameterized. We assume that the T wave should be described by a regular and smooth function, i.e. a l^{th} order polynomial function characterized by its coefficients in the vector $\underline{\theta}_i$.

Finally, our model is expressed as :

$$x_i(n) = \alpha_i.s_{d_i}(n) + \alpha_i.f_{d_i}(n;\underline{\theta}_i) + e_i(n) \qquad (2)$$

where i, $i = 1..I$, is the number of realizations, and the variable d_i is the i^{th} PR interval to be estimated up to an unknown constant.

It is obvious that if we do not impose constraints on the estimated delays, we will estimate the signal $\underline{s}$ with a time-lag. That is why, it is necessary to impose that the average of the estimated delays equal a constant. For example, we choose the average of the delays identical to the average of the estimated delays at the end of the first iteration.

In order to estimate the PR intervals, we use the Maximum Likelihood Estimator (MLE). The details of the demonstration are reported in [4].

The noise e_i is an iid gaussian noise with zero mean and a variance σ^2. Thus, for all the observations, i.e. all n, and for all i, we have the likelihood function:

$p(\underline{X};\underline{s},d_i,\underline{\theta}_i,\alpha_i) = \Psi.\exp(-\frac{1}{2\sigma^2}.$

$$\sum_i.\sum_n(x_i(n) - \alpha_i.f_{d_i}(n;\underline{\theta}_i) - \alpha_i.s_{d_i}(n))^2 \qquad (3)$$

The aim is to maximise $p(\underline{X};\underline{s},d_i,\underline{\theta}_i,\alpha_i)$, corresponding to the minimization of the criterion J:

$$J = \sum_i \parallel \underline{x}_i - \alpha_i.s_{d_i} - \alpha_i.f_{d_i}(\underline{\theta}_i) \parallel^2 \qquad (4)$$

The minimization of the criterion (4) regards $\underline{s}$ gives :

$$\widehat{\underline{s}} = \frac{1}{I}\sum_k \frac{1}{\alpha_k}(\underline{x}_{k,-d_k} - \alpha_k.f_{d_i}(\underline{\theta}_k))$$

As previously mentioned, we can consider that the T wave is modeled by a function $f(n;\underline{\theta}_i)$ which is, for example, a l^{th} order polynomial characterized by its coefficients $\underline{\theta}_i$:

$$f_{d_i}(\underline{\theta}_k)[n] = \sum_{l=0}^{L}\theta_k[l].(n-d_i)^l$$

Also, in order to assert that the model is identifiable, we add a new non restrictive constraint that is the average of the functions $f(\underline{\theta}_k)$ is zero.

Finally, the criterion to be minimized is J:

$$J = \sum_i \parallel \underline{x}_i - \alpha_i.f_{d_i}(\underline{\theta}_i) - \frac{\alpha_i}{I}\sum_{k=1}^{I}\frac{1}{\alpha_k}x_{k,d_i-d_k} \parallel^2 \quad (5)$$

When we develop this criterion (6), we can observe, for example for d_i, that it appears especially in the i^{th} term and is present only once in the others terms. Then, we can make the approximation that in the others terms the d_i's influence is negligible; only the i^{th} term in the criterion is then considered for the i^{th} step. Then, thanks to this approximation, for the i^{th} step, the criterion to be minimized is:

$$J = \parallel \underline{x}_i - \alpha_i.f_{d_i}(\underline{\theta}_i) - \frac{\alpha_i}{I}\sum_{k=1}^{I}\frac{1}{\alpha_k}x_{k,d_i-d_k} \parallel^2 \qquad (6)$$

Then, the optimization can use an iterative algorithm. In the first time, we define a reference wave, a template, which is the average of the observations which do not contain T wave considering that all the α_i equal 1. Thanks to the MLE, for the first step (i.e. $i = 1$), we estimate the coefficient $\widehat{\alpha}_1$, the coefficient $\widehat{\underline{\theta}}_1$ of the polynomial function and the delay $\widehat{d_1}$. We adjust the first observation by substraction of the polynomial function and realign it using the estimated delay. A new template is computed in order to be used in the next steps. If necessary, the process can be iterated depending on the convergence of the algorithm. Thanks to this model, we take into account the overlapping T wave. Then, the PR intervals are produced up to an unknown constant by the estimated delays $\widehat{d_i}$.

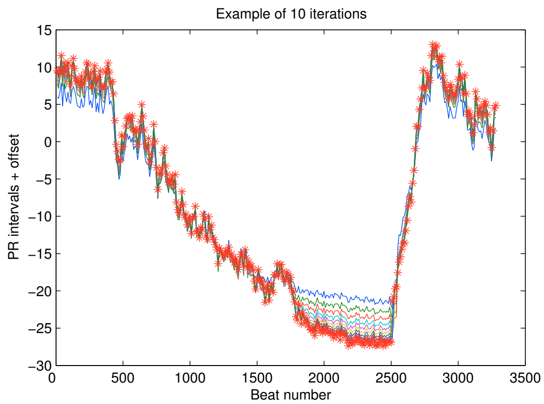

Figure 1. PR intervals up to an unknown constant for one subject - Representation of 10 iterations of the algorithm - The 10^{th} iteration is represented by the line with asterisk marker.

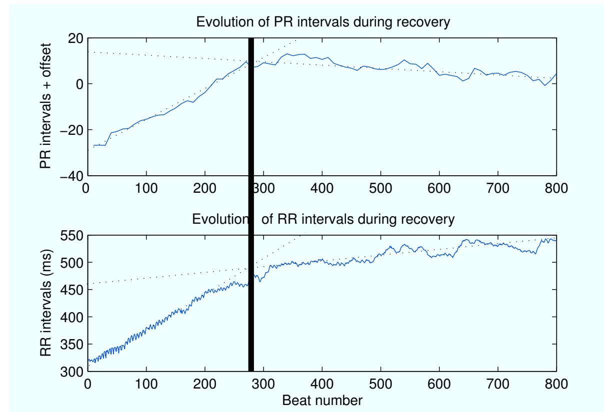

Figure 2. Evolution of PR and RR intervals during recovery - Abrupt change of slope at the same time occurrence

3. Results

The previous method which is a generalization of the Woody's method regards optimality and modeling, is applied to real data. Here, we present the results of the delays estimation method applied on real ECG recordings from 12 healthy men (including 6 athletes). The subjects performed a graded exercise test on a cycle ergometer.

Before the PR estimation, two pre-processing methods permit us to estimate the position of R waves and a coarse P wave localization. First, a threshold technique applied on the high-pass filtered and demodulated ECG, refines the estimation of the R waves times of occurrence. Then, we obtain segments including each P wave and its corresponding R wave, in sequence. We consider the segments as observations $\underline{x}_i$ in the model (2).

By computation of the method, we estimate the coefficients of the polynomial function representing the T wave and we obtain the $\widehat{d}$'s corresponding to the PR intervals up to an unknown constant. The algorithm is iterated until convergence. On pseudoreal simulations of ECG, it has been observed that the better order for the polynomial function was the first one. This order corresponds to a good balance between bias and variance.

Figure 1 shows an example of the estimated PR intervals. Ten iterations are plotted assuming the algorithm converges at the end. That will be the case for all subjects.

On a real data set, the results exhibit the same trend for PR and RR intervals. Only the recovery period is presented on figure 2 showing evidence of an abrupt change of the slope of the PR intervals which is significantly correlated with the RR'one (r = 0.996 ; p-value < 0.001). Figure 3 shows the scatter diagram which puts in light the relation between the time occurrence of abrupt change of slope of PR and RR intervals during the recovery.

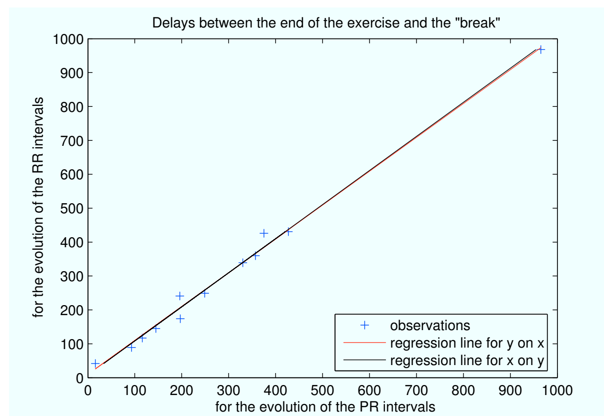

Figure 3. Scatter diagram of the observations for 12 subjects - Relation between the abrupt change of slope for PR and RR intervals; r = 0.996 ; p-value < 0.001

Figure 4 shows a phenomenon of "overshoot" during recovery which is visible only for the 6 athletes : quickly after the end of the exercise, the PR interval's values are higher than those at rest and then decrease tending towards their nominal value. This overshoot is significant thanks to confidence intervals which are computed over 10 samples intervals with p-value < 0.01.

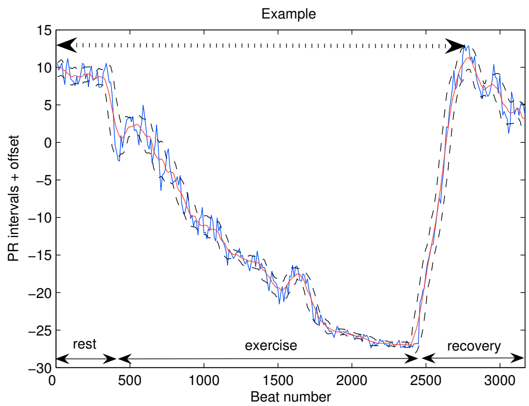

Figure 4. Estimation of PR intervals up to an unknown constant and confidence intervals over 10 samples' window for a p-value < 0.01 - "Overshoot" during recovery

4. Discussion and conclusions

The techniques to estimate the PR intervals were based only on the detection of the maximum of cross correlation function [1], [2]. In this study, it has been presented a new method based on an iterative Maximum-Likelihood approach which generalizes the well known Woody's method [3]. Thanks to this new technique, the estimation of PR interval on effort ECG takes into account the presence of the T wave which overlaps the P one at high heart rate.

On real data set, we note that during the recovery, it exists an abrupt change of slope of the PR intervals which is significantly correlated with the RR's one. As the exercise ends, the PR and the RR intervals increase piecewise linearly with two different slopes. The location of the slope change is related to each subject. The high correlation between the change of slopes of PR and RR intervals, confirms that the origin of this variation is the same for the two types of intervals. This can be explained at the physiological level by a parasympathetic return and sympathetic withdrawal which are different on the two nodes. Actually, several studies have revealed that the sympathetic and parasympathetic influences on the sinusal and atrioventricular nodes seem to be different [7], even independent [8]. It would seem that the parasympathetic influence works more on the AV node than it does on the sinusal one at the exercise's end.

In conclusion, this technique of time delay estimation which improves the Woody's method, is a good tool to characterize the PR and RR intervals and, including others studies, it would carry out a better knowledge of the neural activity during exercise and recovery in the field of pacemaker's design. Also, an endocavity recording, where we could reliably mesure the PR intervals, could help us to confirme our results and conclusions. However, it exists a lot of limitations for this type of protocol. Furthermore, endocavity investigation is a risky procedure during exercise when heart rate is high.

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