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Correction of Erroneous and Ectopic Beats Using a Point Process Adaptive Algorithm

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Abstract— **We present a new *R-R* interval correction procedure based on a point process model of the human heart beat. The algorithm combines an adaptive point process filter with a set of conditions on the probability of having a beat according to the model. This framework allows for correction of ectopic and erroneously detected beats in an on-line fashion, simultaneous with computation of instantaneous estimates of heart rate and heart rate variability. Results demonstrate the efficacy of the method, and show new heart rate and heart rate variability dynamics corrected for artifacts introduced by incorrect and/or irregular *R-R* intervals.**

I. Introduction

Abrupt changes in the *R-R* interval series may occur due to an ectopic beat or by peak detection errors, when the algorithm misses beats or detects them when there is no event. This creates artifacts in the heart rate variability (HRV) dynamics, which may hide significant trends of cardiovascular control. To date, classification and detection of irregular beats has been mainly achieved by direct human evaluation and, more recently, by automatic filtering techniques [1]-[6]. These standard procedures are somehow efficient, but in most cases they are based on signal processing algorithms that have no connection to the physiology of the heartbeat.

We present a new adaptive recursive algorithm to detect and correct ectopic or erroneous beats, while simultaneously compute instantaneous estimates of heart rate and heart rate variability from electrocardiogram recordings of *R*-wave events. Our approach is based on the point process methods for neural spike train data analysis [7],[8] already used to develop both local likelihood [9] and adaptive [10] heart rate estimation algorithms. We model the stochastic structure in the *R-R* intervals as an inverse Gaussian renewal process and derive from it an explicit probability density characterizing instantaneous heart rate. As discussed in [9],[10], the inverse Gaussian probability density is derived directly from an elementary, physiologically-based integrate-and-fire model. Heart rate and HRV are the first and second moments of this probability density. We then use this definition to construct a point process recursive algorithm able to estimate the dynamics of the renewal model parameters and their time-variant behavior at any time resolution. Irregular and missing beats can be easily identified using this model. In fact, irregular beats supposedly occur when the probability density is very low, whereas it can be detected that a beat is missing if no event is recorded when the probability function is at its maximum values.

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II. Methodology

A. Point Process Model of the Human Heart Beat

In an observation interval $(0,T]$, we define $0<u_1<u_2<,...,<u_n<,...,<u_N\le T$ as the N successive *R*-wave event times detected from an ECG. We assume that given any *R*-wave event u_n, the waiting time until the next *R*-wave event, or equivalently, the length of the next *R-R* interval, obeys an inverse Gaussian probability density $f(t\,|\,u_n,\theta)$ where $t>u_n$. The model is defined, at any time *t*, as

$$f(t\,|\,H_{u_k},\theta)=\left[\frac{\theta_{p+1}}{2\pi(t-u_k)^3}\right]^{\frac{1}{2}}\exp\left\{-\frac{1}{2}\frac{\theta_{p+1}[t-u_k-\mu(H_{u_k},\theta)]^2}{\mu(H_{u_k},\theta)^2(t-u_k)}\right\} \quad (1)$$

where $H_{u_k}=\{u_k,w_k,w_{k-1},\ldots,w_{k-p+1}\}$, $w_k=u_k-u_{k-1}$ is the k^{th} *R-R* interval, $\mu(H_{u_k},\theta)=\theta_0+\sum_{j=1}^{p}\theta_j w_{k-j+1}>0$ is the mean, $\theta_{p+1}>0$ is the scale parameter, and $\theta=(\theta_0,\theta_1,\ldots,\theta_{p+1})$.

The probability density in (1) characterizes the stochastic properties of the *R-R* intervals, and represents the instantaneous probability of having a heart beat given the previous beat.

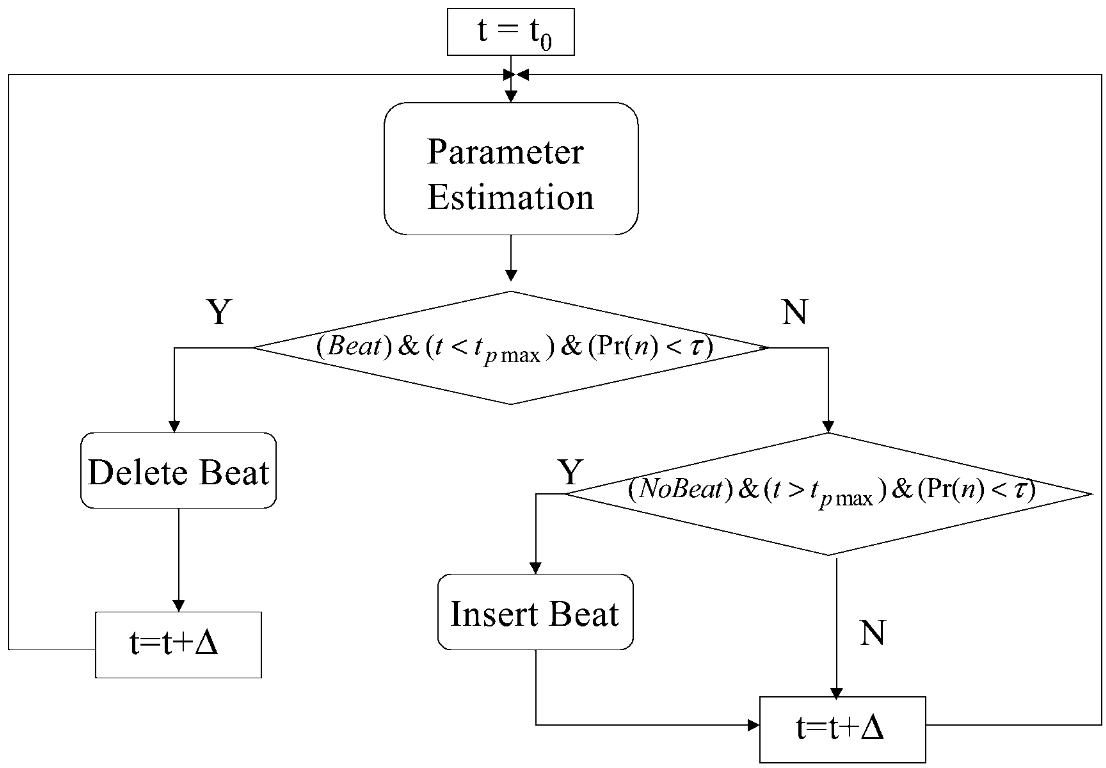

Fig. 1. Flow diagram of the estimation analysis with simultaneous correction of erroneous and missed beats.

Heart rate can be defined as the reciprocal of the *R-R* intervals. Therefore, for any $t > u_n$, we can define $r = c(t - u_n)^{-1}$ as the HR random variable, where $t - u_n$ is the waiting time until the next *R*-wave event, and $c = 6 \times 10^4$ msec/min is the constant that converts the *R-R* interval measurements recorded in milliseconds into HR measurements in beats per minute (bpm).

B. Adaptive Point Process Filter Algorithm

We choose K large, and divide $(0,T]$ into K intervals of equal width $\Delta = T/K$. The adaptive parameter estimates will be updated at $k\Delta$ for $k = 1,...,K$. The adaptive point process filter follows the derivation in [10]. The steps in the recursive algorithm update both the θ parameters and the posterior variance by defining first and second order instantaneous gradients of the conditional intensity function. The adaptive algorithm is different from the approach described in [9]. In the former formulation, the real-time update was based on a local maximum likelihood procedure and needed at least a 60 sec window of data for each update. The local likelihood procedure is used in the new adaptive formulation only to estimate the initial values of the θ parameters.

The heart rate variability indices can be computed directly from the θ parameters. These are: instantaneous mean R-R interval (Mean RR), instantaneous R-R interval standard deviation (StDev RR), instantaneous mean heart rate (Mean HR), and instantaneous heart rate standard deviation (StDev HR):

$$\mu_{RR}(k\Delta) = \mu(H_k, \theta_{k|k}) \tag{2}$$

$$\sigma_{RR}(k\Delta) = [\mu(H_k, \theta_{k|k})^3 \theta_{p+1,k|k}^{-1}]^{\frac{1}{2}} \tag{3}$$

$$\mu_{HR}(k\Delta) = \mu^*(H_k, \theta_{k|k})^{-1} + {\theta^*_{p+1,k|k}}^{-1} \tag{4}$$

$$\sigma_{HR}(k\Delta) = \left[\frac{2\mu^*(H_k, \theta_{k|k}) + \theta^*_{p+1,k|k}}{\mu^*(H_k, \theta_{k|k}) \cdot {\theta^*_{p+1,k|k}}^2} \right]^{\frac{1}{2}} \tag{5}$$

where $\theta_{k|k}$ is the point process adaptive filter estimate of θ at time $k\Delta$, $\mu^* = c^{-1}\mu$ and $\theta^*_{p+1} = c^{-1}\theta_{p+1}$.

C. The Beat Correction Algorithm

The algorithm we have developed is able to infer the correct information by deleting the erroneous beats and/or by placing additional beats at the time where the probability indicated by the model is highest. Beat correction and parameter estimation are performed simultaneously. The algorithm is described by the flow diagram in Fig 1. At each moment in time the algorithm estimates the time of the maximum probability ($t_{p\max}$) of having the next beat as defined by our model in (1). At each time t the program tests two conditions. The first determines if the next beat occurs where the probability is lower than a preset threshold (τ)

and happens before the expected event ($t < t_{p\max}$). If this condition is met, the beat is considered as erroneous or ectopic and is deleted, time is increased ($t = t + \Delta$), and the analysis is performed again. If this condition is not met, if as time is increased the probability of having a beat decreases under the threshold value and no beat has occurred yet ($t > t_{p\max}$), the algorithm places a new beat at the time the probability function is maximized.

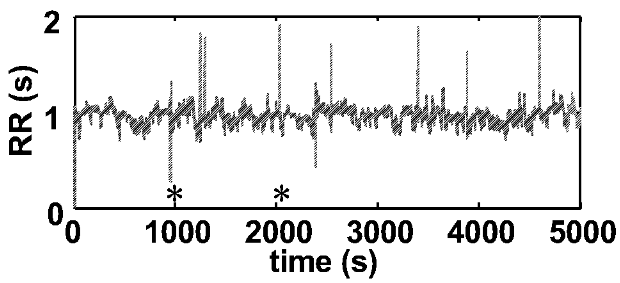

Fig. 2. R-R interval series for a 5000 sec segment recorded from a subject undergoing a sleep protocol before (red trace) and after (blue trace) automatic detection and correction of erroneous and missed beats. Asterisks refer to the two locations on the ECG traces zoomed in Fig. 3.

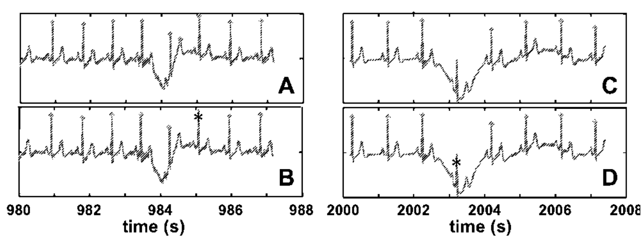

Fig. 3. Example of (A) an erroneously detected beat deleted by the automatic procedure (B), and of (C) missed R-wave corrected by inserting a beat (D). The black asterisks show the corrected beats.

III. Results

We illustrate the method for the *R-R* interval time-series recorded from a sleep protocol and a tilt-table protocol. Fig. 2 shows the resulting corrected *R-R* interval series for a 5000 sec segment recorded from a subject during sleep. In this example several beats where erroneously detected, or were missed, due to movement artifacts. Consequently the beat interval series shows a conspicuous number or very short and very long intervals (red trace). As the analysis is performed, the new resulting series has eliminated all outliers (blue trace) and, as shown in Fig 3, it both deleted beats that do not correspond to *R*-waves on the original ECG (Fig 3A-B), and placed missed beats where *R*-waves were corrupted by motion artifacts (Fig 3C-D). For this example, the percentage of correct beat detection and replacement was 100%.

Fig. 4 shows results from application of the adaptive filter with and without the correction procedure. In the first subject, very long irregular *R-R* intervals appear when the beats are missed by automatic ECG peak detection (both after 1600s and 2200s in panel A). The sharp variation from one beat to the next seriously affects the stability of the adaptive estimation. Especially in the latter interval, in the attempt to track the sudden change, the mean RR and HR estimates deviate significantly from the expected values, whereas both standard deviations increase abruptly. As the R-R interval values go back to the physiological range, the algorithm's instability impedes a rapid convergence of the estimates back to those values, and the perturbation due to the erroneous intervals propagates as long as 250s before the estimates can stabilize again. The adaptive algorithm with the correction procedure, run with identical parameter and covariance matrix initialization (panel B), efficiently tracks the heart rate and heart rate variability dynamics. In the second subject, a higher number of irregular beats are more uniformly distributed in time, due to a pronounced arrhythmia. In this case, the algorithm without correction (panel C) remains stable in face of the irregularities, but it tracks the mean values by estimating significantly higher variances when compared to the algorithm with correction (panel D).

IV. Discussion

The rationale behind our approach is that a beat is 'suspiciously' irregular if it occurs when the model is predicting a very low probability of having an event at that time. Under this condition, the erroneous/ectopic beat can be removed and/or replaced by the 'expected' beat at the moment in time where the model assigns the highest probability of having an event.

The main advantage of our technique is that it allows for beat correction using a very simple decisional framework, which does not require linear or nonlinear interpolation as in previous methods. The complexity in our algorithm is entirely intrinsic to model selection. That is, different models define different probability functions, which in turn give different beat correction and replacement results. At the same time, model selection is also dependent on the nature of the beats, and it is important to consider all possible causes of beat irregularity. Three main points will be considered to further assess and validate our technique: (a) error propagation assessment, (b) comparisons with other methods on both simulated signals and real data, along the lines described in [5], and (c) a more detailed study of the threshold and the algorithm's parameters to better determine the nature of the irregularity and classify the beats for future analysis.

V. Conclusion

Our proposed method offers a simple, physiologically consistent, model-based procedure for correction and classification of beat interval series. This paradigm, once tested extensively on simulated and real data, could be easily implemented in an on-line monitoring device.

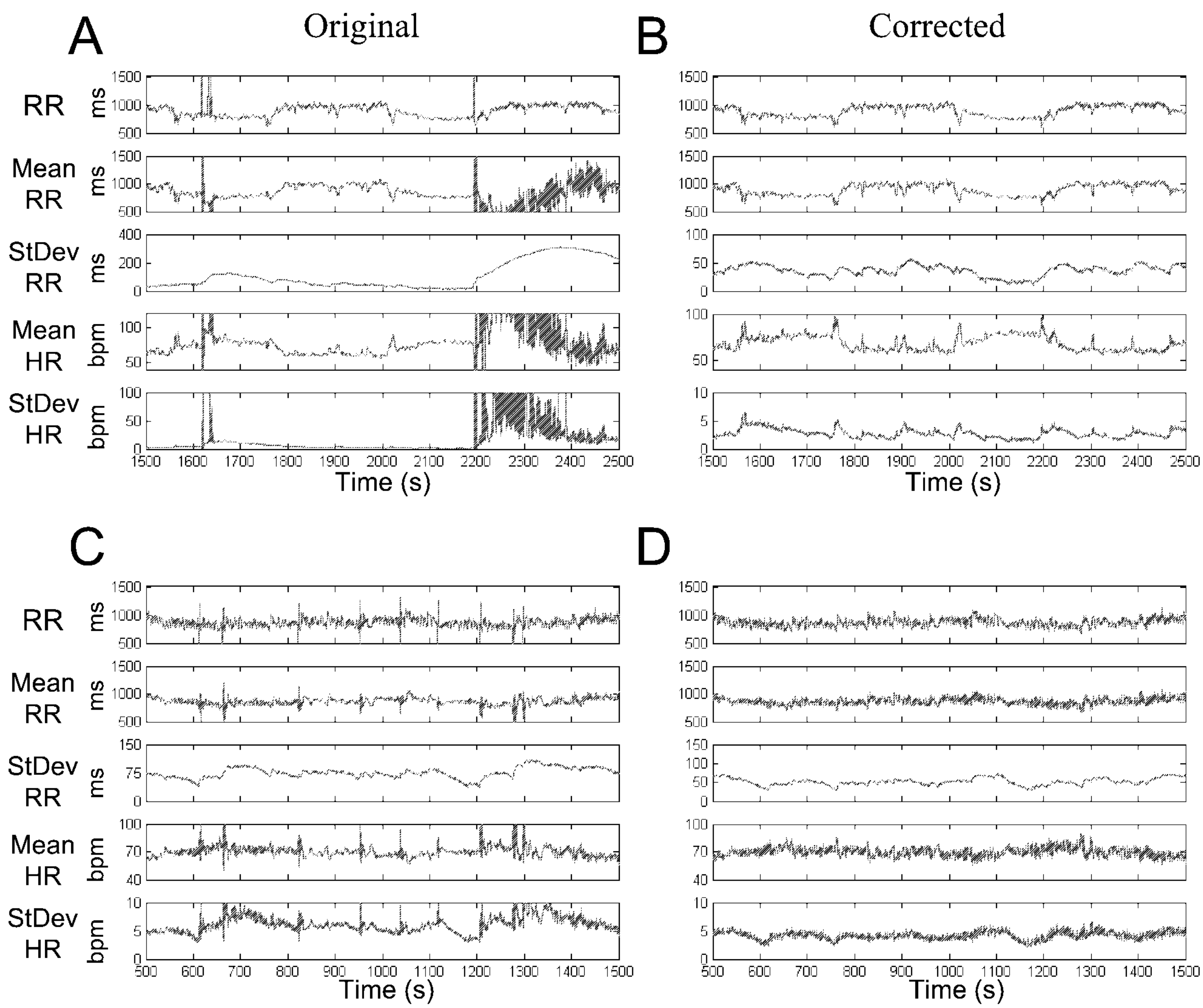

Figure 4. Results from (A,B) a subject under a tilt-table protocol where several beats have not been detected from the ECG, and (C,D) from a subject under the same protocol with pronounced arrhythmias. Original (A,C) and corrected (B,D) *R-R* interval series with respective instantaneous time varying estimates of the mean *R-R* , *R-R* standard deviation, heart rate, and heart rate standard deviation as defined in (2)-(5).

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