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A Point Process Adaptive Filter for Time-Variant Analysis of Heart Rate Variability

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Abstract—**Estimating time-variant heart variability indices from R-R interval beat series has been widely investigated by current research involving cardiovascular control. Most of the currently accepted approaches in time-variant heart rate analysis ignore the underlying discrete structure of human heart beats, and usually require minutes of data. We derive an adaptive point process Bayes' filter based on a statistical model which considers the stochastic structure of heart beat intervals as a point process. From the explicit inverse Gaussian probability density describing heart rate and heart rate variability we are able to extract and recursively update, at any time resolution, a set of indices related to the first and second moments of this probability density. We apply our algorithm in an analysis of human heart beat intervals from a tilt-table experiment. Our results describe real instantaneous estimates of heart rate variability and may have important implications for research studies of cardiovascular and autonomic regulation. Our algorithm is easy to implement for on-line analysis of heart rate variability in the intensive care unit, operating room or labor and delivery suits.**

Keywords—**Heart rate, heart rate variability, time-variant, adaptive filters, stochastic processes, inverse Gaussian.**

I. Introduction

Heart rate is measured in every physical examination and is monitored continuously in patients under anesthesia, those receiving care in the intensive care unit as well as in fetuses during labor. Heart rate variability is an important quantitative marker of cardiovascular regulation by the autonomic nervous system [1-7]. Indices derived from non-invasive monitoring of the heart beat that measure moment to moment the integrity of the cardiovascular system are one of the main goals of current research involving the cardiovascular system. Most of current methods have calculated indices of heart rate variability assuming the number of R waves considered describe a stationary process, therefore preventing temporal localization of sudden changes in cardiac control. Several methodologies have been recently developed to overcome this limitation. All these methods had to deal with the point process nature of the R-R signal, and either had to interpolate the beat series to the desired temporal resolution [8,9], or couldn't consider parameters' updates at a temporal resolution smaller than the length of two consecutive R-R intervals [10-14].

We present a new adaptive recursive algorithm that may be used to 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 [15-17] already used to develop our local likelihood heart rate model [18]. 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. Heart rate and heart rate variability are simply the first and second moments of this probability density. We then use this definition to construct a point process recursive algorithm which is able to estimate the dynamics of the renewal model parameters and their time-variant behavior at any time resolution.

II. Methodology

A. Heart Rate Probability Model

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

$$f(t\,|\,u_k,\theta)=\left[\frac{\theta_2}{2\pi(t-u_k)^3}\right]^{\frac{1}{2}}\exp\left\{-\frac{\theta_2(t-u_k-\theta_1)^2}{2\theta_1^2(t-u_k)}\right\}, \qquad (1)$$

where $\theta=(\theta_1,\theta_2)'$, $\theta_1>0$ and $\theta_2>0$.

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.

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 $c=6\times10^4$ msec/min is the constant that converts the *R-R* interval measurements recorded in milliseconds into HR measurements in beats per minute (bpm)

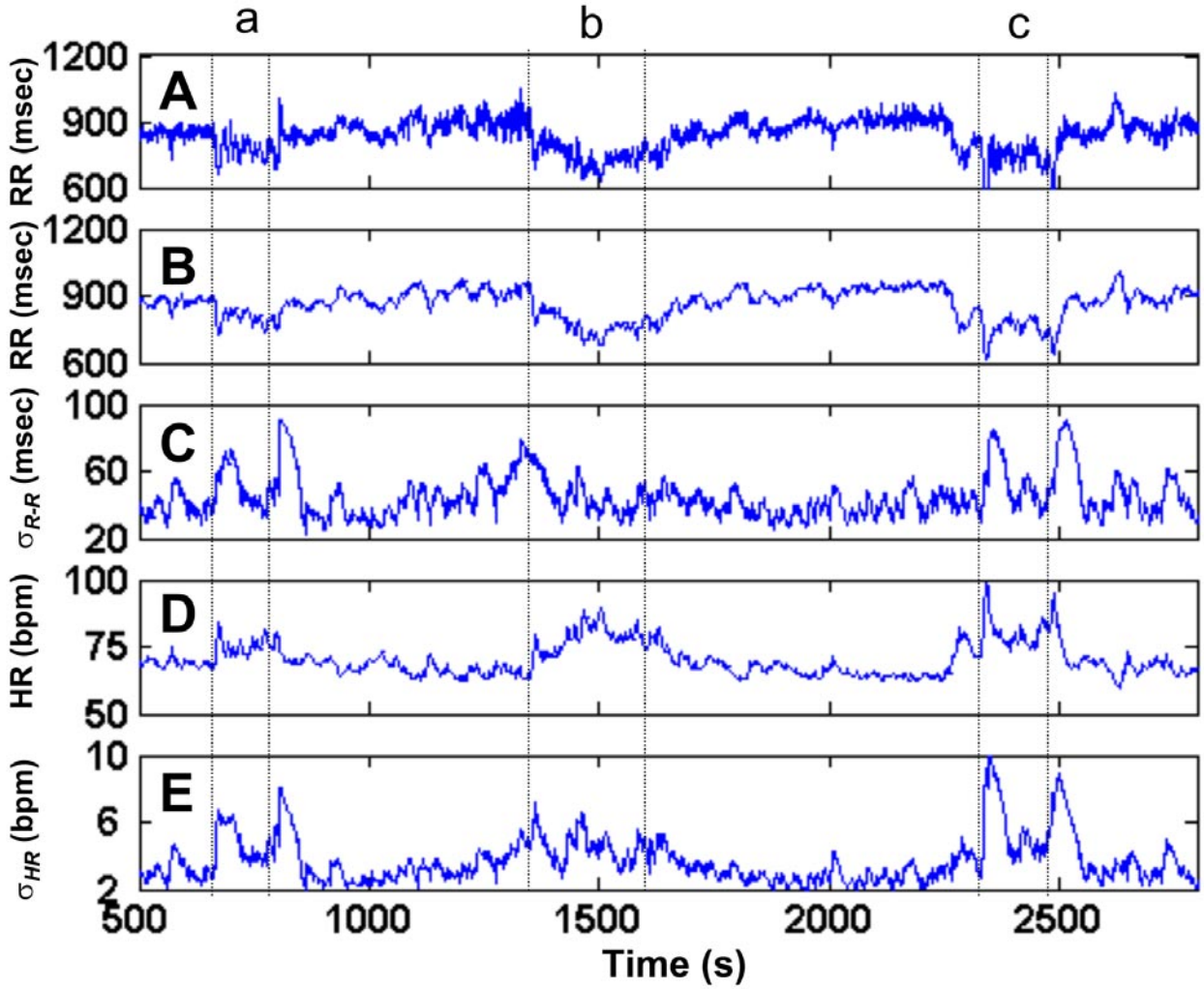

Fig. 1. *Instantaneous time-variant estimates of heart rate.* ***A****. Original R-R interval beat series.* ***B.*** *mean R-R interval,* ***C****. R-R interval variance,* ***D.*** *mean heart rate, and* ***E.*** *heart rate variance derived from our adaptive algorithm. The three coupled vertical dotted lines show the transition periods from supine to upright position, and back to supine, for (a) rapid tilt, (b) slow tilt, and (c) stand up.*

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 $k = 1,...,K$. Given our heart rate probability model, we can define the conditional intensity function as

$$\lambda(t \mid u_{n_t}, \theta_t) = \frac{f(t \mid u_{n_t}, \theta_t)}{1 - \int_{u_{n_t}}^{t} f(u \mid u_{n_t}, \theta_u) du}, \qquad (2)$$

The adaptive point process filter follows the derivation in [1,2]. 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 [18]. 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 calculated directly from the θ parameters. These are: instantaneous mean R-R interval, instantaneous R-R interval variance, instantaneous mean heart rate, and instantaneous heart rate variance (shown in Fig. 1 for our results).

III. Results

We apply our adaptive approach in an analysis of human heart beat intervals from a tilt-table experiment. The protocol began with the subject lying supine for five minutes, after which, the subject underwent 3 types of up-

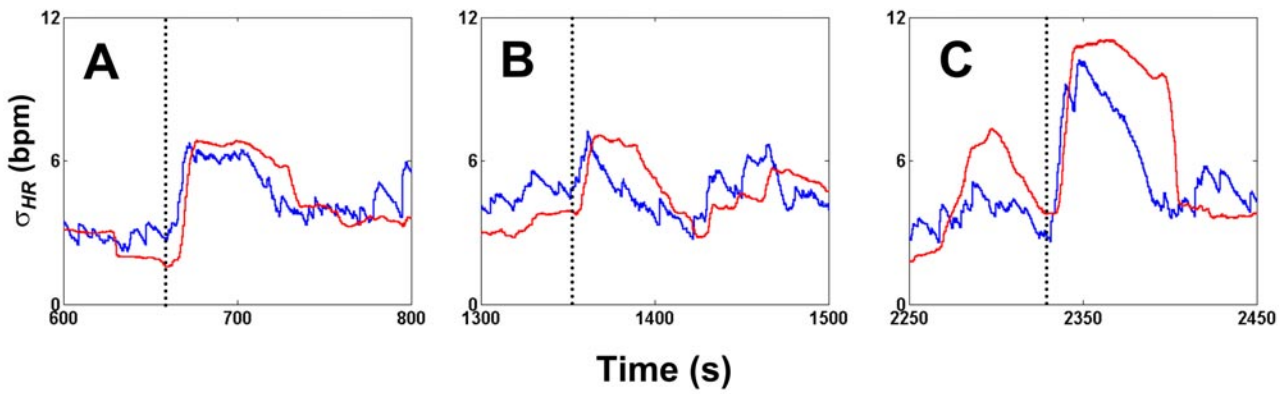

Fig. 2. *T*ime-series of the instantaneous heart rate variance (blue lines) and of the variance estimated considering the inverse R-R intervals contained in a shifting 60 sec time window (red lines). Both series are derived from the *R–R* intervals considered in Fig. 1, plotted for 200 seconds before and after (A) fast tilt , (B) slow tilt, and (C) stand up. The moment of tilt is indicated by the vertical dotted lines. Note the faster changes of the new adaptive estimates

down tilt pairs. The tilt pairs were: rapid up (down) tilts in which the tilt table moved from horizontal (vertical) to vertical (horizontal) in less than 3 sec; slow up (down) tilts in which the tilt table moved from horizontal (vertical) to vertical (horizontal) in approximately 1 min; and stand-ups (lies-supine) in which the subject stood up immediately supporting his or her own weight (lies supine immediately from having been standing supporting his or her own weight) [19].

Figure 1 shows the time-series of the heart variability parameters calculated by the adaptive algorithm applied to the *R-R* interval data (Fig. 1A) from one continuous recording of the tilt protocol. Description of our results is mainly aimed at emphasizing the ability of our analysis to track the dynamic changes, since their faster dynamics allow to differentiate the three gravitational stress procedures.

The time courses of the mean *R–R* intervals and the mean heart rate series follow the well documented patterns of cardiovascular response to orthostatic stress [19-21]. In contrast, the R-R variance time courses, and more markedly the heart rate variance time courses, reveal new patterns of dynamics, in particular the sharp increase in the heart rate variance immediately after standing up.

To analyze more closely the ability of the adaptive algorithm to track the fast heart rate variability changes during the gravitational transients we zoom in time and we visually compare (Fig.2) the time-series of the instantaneous heart rate variance derived from the *R–R* intervals (blue lines) with the standard deviation of the series of the inverse R-R intervals contained in a shifting 60 sec time window (red lines). Clearly our estimates show significantly faster changes, especially right after tilt. The windowed variances are not able to follow fast dynamics because their estimates depend on data as old as 60 seconds. This is the main limitation of most time-variant algorithms, which have to trade off between the need of data to calculate reliable estimates with the objective of having estimates that can track very fast changes.

IV. Discussion

Current methods designed to address non-stationarity apply time-varying methods to *R-R* [9,10] or heart rate [8,11] time series obtained by interpolating respectively the *R-R* interval or the reciprocal of the *R–R* interval beat series. On the other hand, methods that do not interpolate, typically do not consider updates at temporal resolutions smaller than two consecutive *R-R* intervals [12-14].

Our approach, based on the point process methods for neural spike train data analysis [15-17] computes instantaneous estimates of the heart rate variability indices because it can compute sequential updates at any desired time resolution, obviating the need for interpolation. The key feature of our model construction that makes this computation possible is that the point process is defined in continuous time. Because non-stationarity is a physiological property of the *R–R* interval series, we model this feature as a stochastic process with time-varying parameters. The analysis is equally valid for stationary and non-stationary conditions.

Our analysis of the heart beat interval series from the tilt table study show that our indices of heart rate variability provide new information about instantaneous heart rate dynamics. In particular, the sharper increase in the heart rate variance immediately after standing up, that persists for 20 seconds or more before returning to baseline, suggests that this new index may be associated not with autonomic states but instead with the heart rate modulation response to an increase in venous return due to leg muscle contraction as the subject assumes an upright posture This result suggests the new heart rate variance index could be considered as a potential non-invasive measure of cardiac output or total peripheral resistance [19,21].

V. CONCLUSIONS

We derived an explicit probability model for heart rate under the assumption that the stochastic properties of R-R intervals are governed by an inverse Gaussian renewal model. Based on this model, we used an adaptive point process procedure to estimate instantaneous time-variant heart rate variability indices, and we demonstrated the ability of our method to track instantaneous dynamics in autonomic regulation of the cardiovascular system in a tilt table protocol. Our framework gives a more physiologically sound representation of the stochastic structure in heart rate than those provided by current definitions and analysis methods. The adaptive algorithm can update the heart rate variability estimates at any time resolution, obviating the need for interpolation, and can track fast dynamics by considering only the actual information at each time step. The dynamics of our indices of heart rate variability may be useful in characterizing normal and pathological conditions of cardiovascular control and regulation.

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